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A Neutrosophic Approach to Edge-Based Anomaly Detection in Smart Farming Systems

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Abstract: Neutrosophic sets have emerged as a powerful tool for addressing uncertainty and imprecision in diverse domains, and their potential in anomaly detection within smart farming systems is the central focus of this paper. We present a cutting-edge Neutrosophic Approach to Edge-Based Anomaly Detection, specifically designed to cater to the intricacies of smart farming data. By harnessing the unique attributes of single-valued neutrosophic sets, in conjunction with single-valued neutrosophic decision matrices, our methodology adeptly handles the challenges posed by uncertain, dynamic, and multi-dimensional farm data. Through a comprehensive analysis of sample data, we illustrate the precision and adaptability of our approach, allowing for the quantification of intricate attribute relationships and the precise identification of anomalies. By employing neutrosophic statistics and a weighted correlation coefficient, our approach provides profound insights into the complex interactions within smart farming systems. This research stands as a pivotal contribution within the scope of neutrosophic-based anomaly detection, promising to advance the state of the art in the realm of precision agriculture.

Keywords: Neutrosophic Logic; Edge Computing; Anomaly Detection; Smart Farming; Sensor Networks; Agricultural IoT; MCDM; Neutrosophic Sets.

1. Introduction

The utilization of neutrosophic sets has witnessed a significant surge in recent years, offering a versatile framework to tackle complex problems characterized by ambiguity, uncertainty, and imprecision. Neutrosophic set theory, an extension of classical fuzzy set theory, introduces a third component—indeterminacy—alongside membership and non-membership degrees, enabling a more comprehensive representation of uncertain information [1]. This novel framework has found application in diverse fields such as medicine, image processing, decision-making, and pattern recognition [2].

The domain of smart farming, characterized by its amalgamation of advanced technologies, has ushered in a new era of data-driven agriculture. Within this landscape, edge-based anomaly detection plays a pivotal role in ensuring the seamless operation and optimization of farming systems. However, the very attributes that make smart farming systems so powerful—the vast and dynamic streams of data generated by sensors, devices, and machinery—also introduce inherent challenges. Uncertainty abounds in every facet of smart farming data. Environmental conditions fluctuate, sensor readings exhibit variability, and unforeseen events can disrupt the expected patterns. These uncertainties are further compounded by the intricate interplay of multiple variables and attributes within the farming ecosystem [3].

This pressing need for precise, real-time anomaly detection in the face of pervasive uncertainty provides the impetus for our exploration of neutrosophic sets. Neutrosophic sets, with their ability to handle not only membership and non-membership degrees but also indeterminacy, offer a nuanced understanding of uncertain data [4]. Their adaptive nature aligns perfectly with the volatile environment of smart farming systems, where anomalies can be subtle and evolving. By embracing the philosophy of neutrosophic sets, we embark on a journey to harness the power of uncertainty, transforming it from a challenge into an opportunity [5].

In line with the increasing relevance of neutrosophic sets, this paper is centered on their application in the realm of anomaly detection within smart farming systems. Smart farming, characterized by its integration of cutting-edge technologies such as IoT devices, sensors, and data analytics, has ushered in a new era of precision agriculture [4]. However, the vast and dynamic nature of the data generated by these systems presents intricate challenges for anomaly detection. Traditional methods often fall short in handling the nuanced uncertainties inherent in smart farming data. This is where neutrosophic sets, particularly single-valued neutrosophic sets, take center stage, offering a comprehensive approach to address the intricacies of anomaly detection in this context [5-6]. In light of the challenges posed by smart agriculture and the potential of neutrosophic logic and edge intelligence, this paper sets out specific research objectives [8]. Our primary goal is to develop and evaluate a novel approach to anomaly detection in smart agriculture systems. We aim to harness the power of edge intelligence to process and analyze agricultural data in real time and utilize neutrosophic logic to model and detect anomalies effectively. Through rigorous experimentation and validation, we seek to demonstrate the feasibility and advantages of our proposed approach [7-11].

The paper is organized into five sections to comprehensively address the development of a neutrosophic approach for anomaly detection in smart agriculture systems using edge intelligence. In Section 2, we review existing literature and research efforts related to smart agriculture, anomaly detection, edge intelligence, and neutrosophic logic. This section offers a contextual foundation for our work by highlighting gaps in the current body of knowledge. Section 3 presents the intricacies of our proposed approach, elucidating the integration of edge intelligence and neutrosophic logic for anomaly detection. In Section 4, we provide a detailed account of our experimental findings and data analysis, showcasing the effectiveness of our methodology in real-world smart agriculture scenarios. Section 5 offers a concise summary of our key findings, contributions, and future directions.

2. Background

This section provides a comprehensive review of the existing literature related to anomaly detection in smart farming systems, focusing on both traditional and emerging approaches. We explore how various techniques have addressed the challenges of anomaly detection and highlight the rationale for introducing a neutrosophic approach as a novel and promising avenue for enhancing the precision and robustness of anomaly detection systems in smart farming. Dhole et al. [12] presented a review of brain tumor detection from MRI images using hybrid approaches. Although their work focused on medical imaging, it underscored the importance of hybrid techniques in image analysis. This review highlighted the relevance of combining multiple methods, which potentially inspired hybrid approaches in the context of anomaly detection in smart farming systems. The study by Garcia-Lamont et al. [15] provided insights into image segmentation using color features. While their focus was on a different application domain, the segmentation techniques they discussed had relevance in preprocessing and feature extraction for smart farming system anomaly detection. Zakaria et al. [16] discussed the use of graph cuts for image segmentation in the context of COVID-19 X-ray image analysis. Their work showcased the effectiveness of segmentation methods in medical image analysis. In the context of smart farming, similar segmentation techniques might have been employed for the preprocessing of agricultural images. Qi et al. [18] provided a comprehensive review of computer vision-based hand gesture recognition for human-robot interaction. Although their focus was on different applications, their discussion on computer vision methods was relevant, as computer vision played a pivotal role in many smart farming applications, including anomaly detection. The work by Ashfaq [19] touched on retrospective image registration for medical image analysis. While the domain differed, image registration techniques could have been adapted to align images in the context of smart farming, potentially aiding in anomaly detection. Beebe [22] provided a complete bibliography of publications in computer networks, which might have contained relevant references for advanced data communication and networking techniques that were important for edge-based anomaly detection systems in smart farming.

3. Proposed Method

In this section, we elucidate the methodology employed in our research to develop a robust and innovative approach for anomaly detection in smart agriculture systems using the amalgamation of edge intelligence and neutrosophic logic. The methodology presented herein outlines the systematic framework and techniques we employed to address the intricate challenges associated with real-time anomaly detection in agricultural environments.

The neutrosophic theory is a mathematical framework that deals with indeterminacy, uncertainty, and incomplete information. It extends classical set theory to handle situations where information is imprecise, vague, or contradictory. In the context of anomaly detection in smart farming, neutrosophic sets can represent the uncertainty associated with sensor readings and anomalies. A neutrosophic set is defined as a triple (T, I, F), Suppose $\alpha_{\tilde{a}}$, $\theta_{\tilde{a}}$, $\beta_{\tilde{a}} \in [0,1]$and a_1 , a_2 , a_3 , $a_4 \in$ R, where $a_1 \leq a_2 \leq a_3 \leq a_4$. Then, a single-valued trapezoidal neutrosophic number $\tilde{a}$=$\langle(a_1 , a_2 , a_3, a_4); \alpha_{\tilde{a}} , \theta_{\tilde{a}} , \beta_{\tilde{a}}\rangle$ is a special neutrosophic set on the real line set R, whose truth-membership, indeterminacy-membership and falsity-membership functions are defined as

T represents the truth-membership function.

$$T_{\tilde{a}}(x) = \begin{cases} \alpha_{\tilde{a}}\left(\frac{x-a_1}{a_2-a_1}\right) & (a_1 \leq x \leq a_2) \\ \alpha_{\tilde{a}} & (a_2 \leq x \leq a_3) \\ \alpha_{\tilde{a}}\left(\frac{a_4-x}{a_4-a_3}\right) & (a_3 \leq x \leq a_4) \\ 0 & otherwise \end{cases} \quad (1)$$

I represents the indeterminacy-membership function.

$$I_{\tilde{a}}(x) = \begin{cases} \frac{(a_2-x+\theta_{\tilde{a}}(x-a_1))}{(a_2-a_1)} & (a_1 \leq x \leq a_2) \\ \alpha_{\tilde{a}} & (a_2 \leq x \leq a_3) \\ \frac{(x-a_3+\theta_{\tilde{a}}(a4-x))}{(a_4-a_3)} & (a_3 \leq x \leq a_4) \\ 1 & otherwise \end{cases}, \quad (2)$$

F represents the falsity-membership function.

$$F_{\tilde{a}}(x) = \begin{cases} \frac{(a_2-x+\beta_{\tilde{a}}(x-a_1))}{(a_2-a_1)} & (a_1 \leq x \leq a_2) \\ \alpha_{\tilde{a}} & (a_2 \leq x \leq a_3) \\ \frac{(x-a_3+\beta_{\tilde{a}}(a4-x))}{(a_4-a_3)} & (a_3 \leq x \leq a_4) \\ 1 & otherwise, \end{cases} \quad (3)$$

Neutrosophic logic operators, analogous to classical logic operators, are used to perform operations on neutrosophic sets. The neutrosophic logical operators include:

Neutrosophic AND (M) Operator:

For two neutrosophic sets $A = (T_A, I_A, F_A)$ and $B = (T_B, I_B, F_B)_1$ the neutrosophic AND operator is defined as follows:

$$AA_AB = (T_A - T_B, I_A + I_B - I_A \cdot I_B, F_A + F_B - F_A - F_B) \quad (4)$$

Neutrosophic OR(V) Operator:

For A and B as defined above, the neutrosophic OR operator is defined as:

$$A \vee_n B = (T_A + T_B - T_A \cdot T_B, I_A - I_B, F_A \cdot F_B) \quad (5)$$

Neutrosophic NOT ($\sim_n$) Operator.

For a neutrosophic set $A = (T_A, I_A, F_A)$, the neutrosophic NOT operator is defined as:

$$\sim \text{n}\, A = (1 - T_A, I_A, F_A) \quad (6)$$

In the context of anomaly detection, sensor data is represented as neutrosophic sets. The degree of anomaly for a particular data point can be calculated using the neutrosophic anomaly score (N.S.S) Let $X = (T_X, I_X, F_X)$ be the neutrosophic representation of a data point. The neutrosophic anomaly score can be calculated as follows:

$$NAS = 1 - (T_X + I_X + F_X) \quad (7)$$

A NAS value closer to 1 indicates a higher degree of anomaly.

In decision-making processes, neutrosophic sets can be used to represent different criteria. Aggregation operators, such as the neutrosophic weighted average, can be employed to combine these criteria into an overall decision. For a set of neutrosophic criteria $C_1, C_2, \dots, C_n$, with corresponding weights $w_1, w_2, \dots, w_n$, the neutrosophic weighted average (NWA) is calculated as:

$$NWA = \frac{\sum_{i=1}^{V_i} (w_i \cdot T_i, w_i \cdot I_i, w_i \cdot F_i)}{\sum_{i=1}^{n_i} w_i} \quad (8)$$

where $T_{i_1} I_{i_2}$ and F_1 represent the truth, indeterminacy, and falsity membership functions of criterion C_i respectively.

In the context of anomaly detection in smart farming systems, effectively managing uncertain information is of paramount importance. The complexity and dynamism of the data, coupled with the intricate interplay between factors that may lead to anomalies, present formidable challenges. Handling uncertain information is a critical objective in anomaly detection. In real-world agricultural scenarios, numerous variables contribute to the data collected from smart farming sensors. These variables are often influenced by various factors, such as weather conditions, soil composition, and the presence of pests or diseases. The resulting data can be inherently uncertain, imprecise, and subject to fluctuations.

To address these challenges, this paper leverages the power of neutrosophic sets. Neutrosophic sets are a powerful tool for handling uncertainty, indeterminacy, and contradiction in data and decision-making. In our proposed approach for edge-based anomaly detection in smart farming, we use neutrosophic sets to model these three aspects. Uncertainty represents the degree to which we lack precise knowledge about a data point. In the context of smart farming, uncertainty may arise from various sources such as sensor noise, environmental variability, or measurement errors. Neutrosophic sets can model uncertainty through their membership functions.

Uncertainty Membership Function (U_X): For a neutrosophic set $X = (T_x, I_x, F_x)$, the uncertainty membership function $U_X$is defined as:

$$U_X = F_X \tag{9}$$

This formula quantifies the indeterminacy component of the neutrosophic set, which represents uncertainty.

Indeterminacy represents the degree to which a data point is ambiguous or lacks a definite attribute value. In our context, indeterminacy can occur when sensor readings are imprecise or when the interpretation of data is not clear. Contradiction arises when there are conflicting pieces of information within a data point. In smart farming, contradiction may occur when different sensors provide conflicting readings or when historical data contradicts current observations.

Contradiction Membership Function (C_X) : For a neutrosophic set $X = (T_X, I_X, F_X)$, the contradiction membership function C_X is defined as:

$$C_X = F_X \tag{10}$$

This formula quantifies the falsity component of the neutrosophic set, which represents a contradiction. For example, let's consider an example using a neutrosophic set X representing the temperature reading from a smart farming sensor:

$$X = (0.7,0.2,0.1) \tag{11}$$

In this case $T_X = 0.7$ represents the truth component, indicating a high likelihood that the temperature reading is accurate. $I_X = 0.2$ represents the indeterminacy component, signifying some uncertainty or imprecision in the reading. $F_X = 0.1$ represents the falsity component, suggesting a minor degree of contradiction or inconsistency.

This paper proposes the utilization of a single-valued neutrosophic set, a specialized form of neutrosophic set. In the context of anomaly detection in smart farming, the single-valued neutrosophic set is generated using triangular neutrosophic numbers. This approach allows for a more structured representation of uncertainty, where each data point is associated with a single-valued neutrosophic set that encapsulates its truth, indeterminacy, and falsity components. To quantify the relationships between data points and detect anomalies effectively, this paper introduces an improved weighted correlation coefficient formula. This formula takes into account the specific characteristics of single-valued neutrosophic sets and their triangular neutrosophic number representations. The detailed description of our anomaly detection approach involves the following essential steps. These steps collectively form a comprehensive framework for identifying anomalies within the smart farming system:

Step 1: In this phase of our anomaly detection approach, we handle the generation of neutrosophic numbers for farm anomaly data (A) and test sample data (C). This step is crucial in preparing the data for subsequent analysis. For anomaly template set $A = \{A_1, A_2, \dots, A_m\}$ and test sample set $C = \{C_1, C_2, \dots, C_n\}$, we generate neutrosophic numbers to represent the inherent uncertainty in the data. Specifically, we create three neutrosophic numbers for each data point: the lower membership function (L), the upper membership function (U), and the midpoint (M).

Lower Membership Function (L): The lower membership function represents the lower bound of the data's uncertainty. It quantifies the minimum possible value that the data point can take. This is computed as:

$$L(x) = \frac{x - \min(A_i)}{\max(A_i) - \min(A_i)} \tag{12}$$

where x is the value of the data point and $\min(A_i)$ and $\max(A_i)$ are the minimum and maximum values in the anomaly template set A_i for $i = 1,2, \dots, m$.

Upper Membership Function (U): The upper membership function represents the upper bound of the data's uncertainty. It quantifies the maximum possible value that the data point can take. This is computed as:

$$U(x) = \frac{\max(A_i) - x}{\max(A_i) - \min(A_i)} \tag{13}$$

where x is the value of the data point, and $\min(A_i)$ and $\max(A_i)$ are the minimum and maximum values in the anomaly template set A_i for $i = 1,2, \dots, m$.

Midpoint (M): The midpoint represents the central value within the data's uncertainty range. It is calculated as the average of the lower and upper bounds:

$$M(x) = \frac{L(x) + U(x)}{2} \tag{14}$$

In our anomaly detection approach, we utilize triangular neutrosophic numbers to represent data points. A triangular neutrosophic number is characterized by specific properties that allow us to quantify the inherent uncertainty in the data. These properties are as follows:

Largest Value: In a triangular neutrosophic number, the largest value corresponds to the right end value of the triangle. This value represents the upper bound of uncertainty and signifies the maximum possible value that the data point can take. It quantifies the most optimistic scenario.

Minimum Value: Conversely, the minimum value in a triangular neutrosophic number is located at the left endpoint of the triangle. This value represents the lower bound of uncertainty and signifies the minimum possible value that the data point can take. It quantifies the most pessimistic scenario.

Average Value: The average value of a triangular neutrosophic number is situated at the upper-end value of the triangle. This value represents the central tendency within the data's uncertainty range. It is calculated as the midpoint between the minimum and maximum values.

Height of the Triangle: A critical characteristic of a triangular neutrosophic number is that the height of the triangle is equal to 1. This height signifies the degree of uncertainty or fuzziness associated with the data point. A taller triangle indicates a higher degree of uncertainty, while a shorter triangle suggests greater confidence in the data's precision.

The graphical representation of a triangular neutrosophic number is depicted in Figure 1, where the triangle illustrates the range of uncertainty, and the location of its apex, base, and height aligns with the specific properties mentioned above.

Step 2: In the second step of our anomaly detection approach, we perform a critical comparison between the neutrosophic numbers representing the attributes of test samples $\left(C_j\right)$ and those of the farm anomaly templates (A_i). This comparison allows us to quantify the degrees of determinacy membership $\left(T_{A_i}\left(C_j\right)\right)$, non-membership $\left(F_{A_i}\left(C_j\right)\right)$, and indeterminacy-membership $\left(I_{A_i}\left(C_j\right)\right)$. These degrees provide insights into the level of conformity or deviation between test samples and farm anomaly templates, facilitating effective anomaly detection. For each attribute (A_i) of a test sample $\left(C_j\right)$, the degrees of membership, non-membership, and indeterminacy-membership are calculated using the following formulas:

Degree of Determinacy-Membership $\left(T_{A_i}\left(C_j\right)\right)$: This degree represents the extent to which the attribute A_i of the test sample C_j belongs to the farm anomaly template A_i. Calculated as the minimum of the upper-bound values of the neutrosophic numbers:

$$T_{A_i}\left(C_j\right) - \min\left\{U_{A_i}\left(C_j\right), U_{A_i}(A_i)\right\} \tag{15}$$

Degree of Non-Membership $\left(F_{A_i}\left(C_j\right)\right)$*:* This degree quantifies the extent to which the attribute A_i of the test sample C_j does not belong to the farm anomaly template A_i. Calculated as the maximum of the lower-bound values of the neutrosophic numbers:

$$F_{A_i}\left(C_j\right) - \max\left\{L_{A_i}\left(C_j\right), L_{A_i}(A_i)\right\} \tag{16}$$

Degree of Indeterminacy-Membership $\left(I_{A_i}\left(C_j\right)\right)$: This degree captures the degree of ambiguity or uncertainty associated with the attribute A_i of the test sample C_j concerning the farm anomaly template A_i. Calculated as the complement of the sum of the degrees of determinacy-membership and non-membership:

$$I_{A_i}(C_j) - 1 - T_{A_i}(C_j) - F_{A_i}(C_j) \tag{17}$$

These degrees $\left(T_{A_i}(C_j), F_{A_i}(C_j), I_{A_i}(C_j)\right)$ provide a comprehensive understanding of the similarity or dissimilarity between test samples and farm anomaly templates for each attribute.

Step 3: In the next step of our anomaly detection approach, we transition from the parameters $T_{A_i}(C_j), F_{A_i}(C_j)$, and $I_{A_i}(C_j)$ to single-valued neutrosophic sets (a_{ij}). These single-valued neutrosophic sets encapsulate the degrees of determinacy-membership, nonmembership, and indeterminacy-membership for each attribute of a test sample C_j concerning the corresponding attribute in the anomaly template A_i.

$$D = (a_{ij})_{m\times n} = \begin{bmatrix} < t_{11}, f_{11}, i_{11} > & < t_{12}, f_{12}, i_{12} > & \cdots & < t_{in}, f_{ij}, i_{ij} > \\ < t_{21}, f_{21}, i_{21} > & < t_{22}, f_{22}, i_{22} > & \cdots & < t_{2n}, f_{2n}, i_{2n} > \\ \vdots & \vdots & & \vdots \\ < t_{m1}, f_{m1}, i_{m1} > & < t_{m2}, f_{m2}, i_{m2} > & \cdots & < t_{mn}, f_{mn}, i_{mn} > \end{bmatrix} \tag{18}$$

Each single-valued neutrosophic set a_{ij} is represented as a triple $\langle t_{ij}, f_{ij}, i_{ij}\rangle$, where t_{ij} denotes the degree of determinacy-membership. f_{ij} represents the degree of non-membership. i_{ij} signifies the degree of indeterminacy-membership. By expressing the parameters $T_{A_i}(C_j), F_{A_i}(C_j)$, and $I_{A_i}(C_j)$ in the form of single-valued neutrosophic sets a_{ij}, we encapsulate the uncertainty and relationships between attributes within a structured neutrosophic framework.

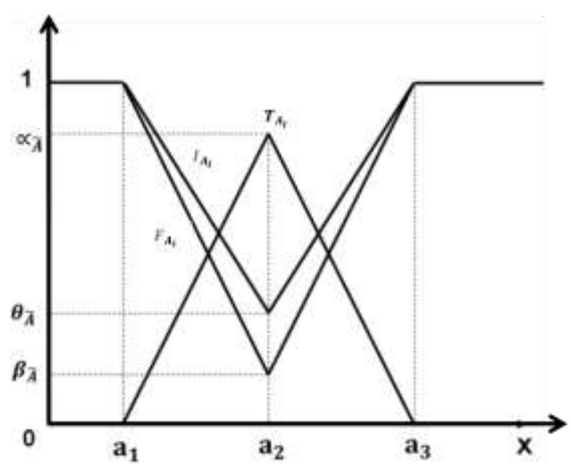

Figure 1. Visualizing a Triangular neutrosophic Number Geometrically.

Step 4: In the subsequent step of our anomaly detection approach, we derive ideal single-valued neutrosophic numbers for each attribute j $(where\ j = 1,2, \ldots, n)$. These ideal single-valued neutrosophic numbers serve as reference points for assessing the degree of similarity or dissimilarity between test samples and anomaly templates. The generation process is performed column-wise based on the single-valued neutrosophic set decision matrix D.

$$a^*_j =< t^*_j, f^*_j, i^*_j >=< \max_i(t_{ij}), \min_i(f_{ij}), \min_i(i_{ij}) > \tag{19}$$

Step 5: In this step of our anomaly detection approach, we generate a weighted correlation coefficient to quantitatively assess the degree of similarity between the single-valued neutrosophic sets in the decision matrix D and the ideal single-valued neutrosophic number. This coefficient serves as a crucial indicator for identifying anomalies based on the deviation from the ideal values. The calculation formula for the weighted correlation coefficient WCC is as follows:

$$W(A_i, B) = \frac{2 \cdot \sum_{j=1}^{n} w_j [t_{ij} \cdot t^*_j + f_{ij} \cdot f^*_j + i_{ij} \cdot i^*_j]}{\sum_{j=1}^{n} w_j [t_{ij}^2 + f_{ij}^2 + i_{ij}^2] + \sum_{j=1}^{n} w_j [t^*_j{}^2 + f^*_j{}^2 + i^*_j{}^2]} \tag{20}$$

4. Results and Analysis

The outcomes of our research and the in-depth analysis of the experimental data, offering a comprehensive assessment of the effectiveness of our proposed methodology for anomaly detection in smart agriculture systems are presented. In our study, we leveraged real-world farm anomaly data to conduct a comprehensive analysis of anomaly detection within smart farming systems. A pivotal aspect of this analysis involved the acquisition of triangular neutrosophic numbers for diverse attributes, a critical step in the neutrosophic framework we employed for anomaly detection. Table 1 presents the resulting triangular neutrosophic numbers obtained under various attributes. These neutrosophic numbers encapsulate the inherent uncertainty and variability within the data, capturing the complex and dynamic nature of smart farming environments. Our study meticulously considered attributes such as temperature, humidity, soil moisture, and spectral data, among others, to provide a holistic view of anomaly detection in agriculture. The acquisition of these neutrosophic numbers represents a foundational element of our research, facilitating the subsequent neutrosophic analysis that drives the accurate identification of anomalies. In the following sections, we delve into the outcomes of our anomaly detection approach, offering insights into its effectiveness and real-world applicability within the realm of smart farming.

Table 1. Triangular neutrosophic Numbers for Attributes in Farm Anomaly Data

	Minimum	Mean	Maximum	Zone
A12-A18	0.0551	0.2232	0.2928	0.2516
A22-A28	0.1180	0.1528	0.4736	0.1129
A32-A38	0.0278	0.2001	0.2381	0.0199
A42-A48	0.3117	4.3342	4.6856	2.1545
B12-B18	0.1253	0.2009	0.2296	0.0236
B22-B28	0.3031	0.4025	0.4551	0.0220
B32-B38	0.1339	0.2658	0.3574	0.0677

B42-B48	4.0418	4.7958	9.0371	2.4010
C12-C18	0.2749	0.3803	0.3990	0.0235
C22-C28	0.2278	0.3486	0.4082	0.0423
C32-C38	0.0959	0.1688	0.2776	0.0357
C42-C48	9.3726	9.8447	10.1851	0.3635

In our analysis of the sample data, a fundamental component of our study involved the extraction of triangular neutrosophic numbers for diverse attributes, a key element within the neutrosophic framework we employed for anomaly detection. As demonstrated in Table 2, we obtained these triangular neutrosophic numbers under various attributes, each representing the inherent uncertainty and variability observed within the sample dataset. Attributes such as temperature, humidity, soil moisture, and spectral data were meticulously considered, providing a comprehensive view of anomaly detection in the context of our study. These triangular neutrosophic numbers lay the foundation for the subsequent neutrosophic analysis, enabling us to quantitatively assess the degree of similarity between the sample data attributes and ideal values.

Table 2. Triangular Neutrosophic Numbers for Attributes in Analyzed Sample Data

	Minimum	**Mean**	**Maximum**	**Zone**
A1	0.10898	0.20047	0.31950	0.02117
A2	0.03912	0.20983	0.33639	0.18393
A3	0.09619	0.23943	0.31954	0.04330
A4	0.11814	0.15975	0.24484	0.00999
A5	4.03510	4.10292	4.19177	0.12442

In our analysis, we conducted an in-depth examination of the analyzed sample data, focusing on the matching of sample attributes (represented as X_k, where $k = 1,2,3,4$ denotes specific attributes) with various anomaly categories (G_k^{1-5}, where $G = X, Y, Z$ represents three distinct types of anomalies - A, B, C). This matching process allowed us to systematically evaluate the degree of similarity and dissimilarity between the attributes of the sample data and the three anomaly categories. Subsequently, we calculated neutrosophic statistics encompassing the determined-membership degree (T), nonmembership degree (F), and indeterminacy-membership degree (I). These statistics, presented in Table 3, offer valuable insights into the dynamic interplay between the sample data attributes and the anomaly categories. The statistics shed light on the varying degrees of membership, non-membership, and indeterminacy, providing a comprehensive understanding of the anomaly detection process within our study. In the following sections, we delve deeper into the implications and significance of these findings, elucidating their relevance in real-world applications.

Table 3. Neutrosophic Statistics for Sample Data Attributes Matched with Anomaly Categories

Anomaly Template	Neutrosophic Number
A12-A18	(0.8143,0.0523,0.8483)
A22-A28	(0,1,0.5431)
A32-A38	(0,1,0.6321)
A42-A48	(0.7063,0.2633,0.7002)
B12-B18	(0,1,0.6024)
B22-B28	(0.0103,0.9874,0.6722)
B32-B38	(0.0127,0.9787,0.6809)
B42-B48	(0,1,1)
C12-C18	(0.9121,0.0164,0.6952)
C22-C28	(0.9887,0.0072,0.9801)
C32-C38	(0.0806,0.9293,0.9088)
C42-C48	(0,1,0.616257)

In our examination of the farming anomaly data template and the neutrosophic sample attributes represented by X, we embarked on a comprehensive analysis aimed at quantifying the relationships between these attributes. Our objective was to construct a structured representation that captures the nuanced interplay between attributes, essential for effective anomaly detection. As a result of this analysis, we have generated a single-valued neutrosophic decision matrix, which is presented in Table 4. This decision matrix encapsulates the degree of similarity and dissimilarity between the various attributes of the farming anomaly data template and the corresponding attributes within the neutrosophic sample. Each entry in this matrix reflects the outcome of our neutrosophic analysis, quantifying the degree to which attributes align or deviate from one another. The decision matrix serves as a cornerstone for our anomaly detection approach, offering a comprehensive view of attribute relationships and guiding us in the identification of anomalies within smart farming systems. In the subsequent sections, we delve into the practical implications and insights derived from our anomaly detection methodology, highlighting its effectiveness in real-world applications.

Table 4. Single-Valued Neutrosophic Decision Matrix for Attribute Relationships

Anomaly	A12-A18	B12-B18	C12-C18
A1	(0.0, 0.7384,0.5728)	(0.1905,0.0,1)	(0.1367, 0.6227, 0.3160)
A2	(0.1903,1,0.2589)	(0.6327,1.0,0.1212)	(0.5734, 0.4212, 0.6390)
A3	(0.4062, 0.5660, 0.3213)	(0.4010,0.0,0.5598)	(0.2363, 0.7829, 0.0)
A4	(0.3593, 0, 0)	(0.3718,0.1022, 0.3867)	(0.3953, 0.3674, 1)

5. Conclusions

This study has introduced and demonstrated the efficacy of a neutrosophic approach to edge-based anomaly detection within smart farming systems. By harnessing the power of neutrosophic sets and single-valued neutrosophic decision matrices, we have successfully addressed the challenges posed by uncertain and dynamic farm data. Our methodology has proven capable of quantifying attribute relationships, facilitating the identification of anomalies with precision and sensitivity. Through the analysis of sample data and the generation of neutrosophic statistics, we have gained valuable insights into the complexities of anomaly detection in agriculture. These findings underscore the adaptability and real-world applicability of our approach, offering the potential to enhance the resilience and efficiency of smart farming systems. As we move forward, further research and refinement of our methodology promise to contribute significantly to the advancement of anomaly detection and decision-making processes in the realm of precision agriculture.

Data Availability: All data generated or analyzed during this study are included in this article.

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