Neutrosophic Sets and Systems, Vol. 83, 2025
University of New Mexico

Application of Interval Neutrosophic Logic Model for Diagnosis of Cattle Disease

Lola Safarova [1,2], Dilnoz Muhamediyeva[1], Sokhibjan Muminov [3,*] and Seyyed Ahmad Edalatpanah[4]

[1] Tashkent Institute of Irrigation and Agricultural Mechanization Engineers, National Research University, Tashkent, Uzbekistan; dilnoz134@rambler.ru

[2] Samarkand State University of Veterinary Medicine, Livestock and Biotechnologies, Samarkand, Uzbekistan; lola.safarova.81@inbox.ru

[3] Mamun University, Khiva, Uzbekistan; sokhibjan.muminov@mamunedu.uz

[4] Department of Applied Mathematics, Ayandegan Institute of Higher Education, Tonekabon, Iran. s.a.edalatpanah@aihe.ac.ir

* Correspondence: Sokhibjan.muminov@gmail.com; Tel.: (+99897 788 99 10)

Abstract: In this paper, we propose a method of interval neutrosophic logic for solving the urgent problem of diagnosing cattle diseases under conditions of data uncertainty. Based on the theory of interval neutrosophic sets, an algorithm has been developed that takes into account the degree of likelihood, falsity, and uncertainty, which ensures more accurate modeling and analysis. The main result of the study is the construction of an interval neutrosophic Sugeno model designed to diagnose cattle diseases such as osteodystrophy, ketosis, and hypomicroelementosis. The model demonstrates high efficiency: the diagnostic accuracy reached 92%, which exceeds the results of other methods, including classical Sugeno models and statistical approaches. A comparative analysis of the developed model with alternative methods was carried out, confirming its advantages under conditions of uncertainty and data heterogeneity. The proposed method has the potential for application in veterinary practice, especially in conditions of limited resources, where high diagnostic accuracy and reliability are required.

Keywords: osteodystrophy, secondary osteodystrophy, ketosis, hypomicroselementosis, decision making, expert systems, fuzzy sets, neutrosophic, interval neutrosophic.

1. Introduction

Since 1965, when Zadeh introduced the concept of fuzzy sets, these ideas have found wide application in a variety of fields, helping to handle uncertainties using fuzzy logic. The classical representation of a fuzzy set uses one specific numerical value to express the degree of membership defined in the context of a universal set X. Within the framework of the corresponding fuzzy logic, each statement is associated with a specific numerical value representing the degree of truth. In certain cases, this value itself is uncertain and cannot always be precisely defined by a clear numerical expression. With this in mind, the introduction of fuzzy sets with interval values provides more flexibility in assessing the degree of truth of statements by adding an element of uncertainty.

The concept of interval-valued fuzzy sets is interesting in the context of uncertainty accounting. In such models, interval values are used to determine the range of membership of elements in a fuzzy set, which makes it possible to more flexibly take into account different degrees of uncertainty. Extending traditional fuzzy logic to interval fuzzy logic, at first glance, may seem simple, since it boils down to replacing point values with interval ones. However, this requires careful consideration of issues related to the interpretation and use of intervals within logical operations and inferences. Research related to type-two fuzzy sets and type-two logic is also interesting because it deepens the understanding of the application of fuzzy logic in the context of uncertainty, allowing us to consider situations where the degree of membership in a fuzzy set can be dual or mixed. These studies may lead to new methods for uncertainty analysis and decision making in various fields where fuzzy logic is applied. [4-14].

Intuitionistic fuzzy sets are an extension of the concept of fuzzy sets. They represent a formal generalization of fuzzy sets and an alternative way of representing uncertainty. Formally, intuitionistic fuzzy sets can be equivalent to intervals with fuzzy values, since they both allow for uncertainty and variability in the degree of membership of elements in the set. However, approaches to their use and interpretation may vary slightly depending on the context and specific tasks. [15-17]. In intuitionistic fuzzy sets, unlike classical fuzzy sets, elements can have not only a certain degree of membership in the set, but also a degree of non-membership. This allows for a more accurate and complete description of uncertainty, since each element can have two components: the degree of membership and the degree of non-membership [18-26].

In real-world situations, including those mentioned above, inconsistent information often arises. Intuitionistic fuzzy logic is obviously unable to handle inconsistency, since it typically requires resolving the inconsistency problem in knowledge bases. Two main approaches are commonly used for this: belief checking and paraconsistent logic. The goal of the first approach is to turn an inconsistent theory into a consistent one, either by revising it or by representing it using consistent semantics. On the other hand, the paraconsistent approach allows reasoning in the presence of inconsistencies, since inconsistent information can be obtained or introduced without simplification. Examples of well-known paraconsistent logics are de Costa's W-logic and Belknap's four-valued logic [27-29].

Intuitionistic fuzzy logic usually does not have mechanisms to handle inconsistency, since it requires strict adherence. Two main approaches are commonly used to overcome the problem of inconsistency in knowledge bases: belief checking and paraconsistent logic. The first approach aims to transform an inconsistent theory into a consistent one by revising it or representing it using consistent semantics. The second approach, paraconsistent, allows reasoning in the presence of inconsistencies because inconsistent information can be introduced or obtained without simplification.[30]

Neutrosophy, introduced by Smarandache in 1995, is a branch of philosophy that studies the origin, nature, and scope of neutralities, as well as their interaction with different spectrums of ideas. It includes neutrosophic probability, neutrosophic sets, and neutrosophic logic. In the neutrosophic set (neutrosophic logic), uncertainty is explicitly quantified, and the degree of truth-membership, the degree of uncertainty-membership, and the degree of falsehood-membership are considered independent. This assumption of independence plays an important role in various applications, such as information fusion, where different data from different sensors need to be taken into account together. It is important to note that the neutrosophic set (neutrosophic logic) is different from the intuitionistic fuzzy set (intuitionistic fuzzy logic), where the degree of uncertainty is defined by default [31].

The country is taking enhanced measures to reduce the incidence, treatment, prevention and control of non-communicable diseases of cattle. In the development and improvement of the efficiency of livestock farming, which is the main branch of agriculture, it is important to increase the number of livestock in state, farm and private farms, increase productivity, proper care, protection from various diseases. The control of non-communicable diseases in livestock farms remains ineffective due to the lack of information on cattle treatment, which has led to a significant decrease in meat production. To reduce the impact of non-communicable diseases, detection and early treatment are necessary to prevent significant losses and wider spread of the disease.

In the world, based on mathematical modeling that supports fuzzy logic in fuzzy sets, in particular, in neutrosophic set, research is being conducted aimed at improving, developing and creating computer diagnostic systems in order to identify types of diseases and their causes at an early stage, as well as improving treatment methods in the field of veterinary medicine. In this regard, the construction of models for diagnosing animal diseases based on fuzzy logic and neutrosophic set, the development of algorithms and programs for predicting and diagnosing cattle diseases is one of the important tasks. A significant obstacle to solving the tasks set are internal non-communicable diseases, among which a significant place is occupied by secondary osteodystrophy, ketosis, hypomicroelementosis and osteodystrophy in cattle. One of the main problems is the development of mathematical models based on the diagnosis of the disease and the analysis of experimental data.

In [32], a fuzzy logic approach is used to identify and calculate the absence or involvement of each possible disease with neurological features and sufficiently reduced natural uncertainty regarding the disease diagnosis.

In [33], four horse gaits (walk, sitting trot, ascending trot, gallop) of three horse breeds (Jeju, Warmblood, and Thoroughbred) were classified using Takagi-Sugeno-Kang neuro-fuzzy classifier from wavelet packet transformed data information. In [34], a controller for the brain state index of animals was developed.

Due to the importance of estrus detection for reproductive function, work [35] focused on developing an algorithm using fuzzy sets to predict estrus in dairy cows. [36] used a fuzzy logic method to show the benefits of combining cow activity and the period since last heat to determine whether a cow is in heat or not, reporting an improvement in insemination prediction compared to other methods. In [37], a fuzzy logic model for monitoring the udder health of goats was investigated. In [38], a fuzzy expert system was developed to predict the live weight of hair goats. The fuzzy model can simulate the nature of clinical diagnosis for veterinary medicine. In [39], a fuzzy disease model, disease classification methods, differential diagnosis group, and fuzzy diagnosis model were discussed. Knowledge of animal disease diagnostics is fuzzy, and the creation of a representation and reasoning model for animal diagnosis knowledge based on fuzzy theory can reflect the nature of medical diagnosis to some extent. In the listed works, we did not find developments of fuzzy logic algorithms for diagnosing cattle diseases.

Neutrosophic logic, a group of multi-valued systems that can be considered as an extension of fuzzy logic, is one of the new theories based on the fundamental principles of neutrosophy. The logic of neutrosophy is a new branch of logic that eliminates the shortcomings of fuzzy and classical logic. Some disadvantages of fuzzy relations are the inability to handle contradictory information and the high cost of processing a nonlinear program. In neutrosophic sets, truth and falsity are independent, while in intuitionistic fuzzy sets they are dependent. Neutrosophic logic is capable of manipulating both incomplete and contradictory data. Thus, there is a need to explore the use of neutrosophic logic in various fields, from medical treatment to the role of a recommender system using new advanced computational intelligence methods. The aim of our study is to investigate the possibility of predicting the state of osteodystrophy, secondary osteodystrophy, ketosis and hypomicroelementosis and to build a model for predicting these diseases in cattle using the theory of fuzzy sets and the new theory of interval neutrosophic set.

Qayyum et al . [40] presented generalized interval-valued intuitionistic fuzzy soft expert sets as an extension of classical fuzzy and intuitionistic sets by adding membership degree and rejection degree. These sets demonstrated high flexibility in modeling uncertainty and imprecise information, making them particularly useful for medical diagnostic tasks. The study also proposed Type I, II, and III similarity measures, which were applied to analyze the relationships between medical cases, facilitating the decision-making process and improving the quality of diagnosis.

Narmadhagnanam and Samuel [41] introduced the concept of cut-off ranges for medical diagnostics. This method has been shown to be effective in differentiating between disease classes and removing the uncertainty inherent in common symptoms. The application of cut-off ranges has demonstrated its value as a mechanism for improving the accuracy of diagnostic decisions, especially in problems of analyzing complex symptom data.

Dhanalakshmi [42] proposed coarse neutrosophic sets that include cosine similarity measures for analyzing complex decision-making scenarios in medical diagnostics. These sets allowed achieving accurate results when handling uncertain and contradictory data, which is important for critical areas such as medicine. The innovation allows improving the processes of data evaluation and classification, reducing the likelihood of diagnostic errors.

This study develops these concepts by applying interval neutrosophic sets to veterinary diagnostic problems. Using Sugeno's interval neutrosophic model allows for likelihood, falsity, and uncertainty to be taken into account, making the proposed approach more accurate and robust in real veterinary data.

Motivation and novelty of the study.

Diagnosis of cattle diseases is one of the key tasks of veterinary science, since timely detection and treatment of diseases significantly affects the productivity of livestock farming and the economic sustainability of farms. However, modern diagnostic methods face a number of problems, such as limited information, inconsistency of data and a high degree of uncertainty in clinical indicators. Existing approaches, including classical fuzzy logic models, intuitionistic fuzzy sets and statistical methods, have significant limitations in processing such data. They often do not take into account uncertainty and inconsistency, which reduces their reliability in real veterinary practice.

The main gap in research is the lack of universal models that can effectively work with heterogeneous and noisy data typical for animal diagnostics. To solve this problem, it is proposed to use interval neutrosophic logic, which allows taking into account the likelihood, falsity and uncertainty simultaneously. The novelty of the work consists in the development of the interval neutrosophic Sugeno model for the diagnosis of cattle diseases. This is the first approach using interval neutrosophic logic in veterinary practice to improve the accuracy and reliability of diagnostics. The proposed model is able to significantly reduce the percentage of classification errors and provides veterinary specialists with additional tools for decision-making.

2. Materials and Methods (proposed work with more details)

The interval neutrosophic set is a concept within the neutrosophic theory that can be applied in scientific and medical research. It is a concrete example of a neutrosophic set that has interval values, which makes it useful for describing and analyzing various phenomena and is a tool in solving real-world problems in various fields.Let's say we have a universal space of points, denoted U, with a common element x. The neutrosophical set A can be defined as follows:

Suppose we have a universal space of points, denoted by U, with a common element x. The neutrosophic set A can be defined as follows:

$$A=\left\{x,\langle T_A\left(x\right),I_A\left(x\right),F_A\left(x\right)\rangle \mid x\in U\right\}, \tag{1}$$

where - $T_A\left(x\right),I_A\left(x\right),F_A\left(x\right):U\to]^{-}0,1^{+}[$ functions of belonging to truth, belonging to uncertainty and belonging to falsity, respectively, with $^{-}0\le \sup T_A\left(x\right)+\sup I_A\left(x\right)+\sup F_A\left(x\right)^{\le 3^{+}}$. [43-45] Equation (1) improves the adaptation of the model to real data, taking into account disagreements and uncertainty. Increases the reliability of forecasts in diagnostic problems and justifies the results.

Let U be the universal set of points represented by x. Then the unique neutrosophical fuzzy set $S \subset U$ is defined as follows:

$$S = \{x, \langle T_s(x), I_s(x), F_s(x)\rangle | \in U\} \quad (2)$$

where $T_s(x), I_s(x)$ and $F_s(x)$ denote the functions of belonging to truth, belonging to uncertainty and belonging to falsity, respectively [46].

Let U be a universal set represented by x. The interval neutrosophic set N is represented as follows:

$$N = \{x, \langle T_N(x), I_N(x), F_N(x)\rangle | x \in U\} \quad (3)$$

where $T_N(x), I_N(x), F_N(x)$ - truth membership function, uncertainty membership function and falsity membership function respectively. For each point

$$x \in U, T_N(x), I_N(x), F_N(x) \subseteq [0,1] u 0 \le \sup T_N(x) + \sup I_N(x) + \sup F_N(x) \le 3.$$

For convenience, if

$$T_N(x) = [T_N^L(x), T_N^U(x)]; I_N(x) = [I_N^L(x), I_N^U(x)]; F_N(x) = [F_N^L(x), F_N^U(x)]$$

then $$N = \{x, \langle [T_N^L(x), T_N^U(x)], [I_N^L(x), I_N^U(x)], [F_N^L(x), F_N^U(x)], \rangle | x \in U\} \quad (4)$$

with the condition $0 \le \sup\mathrm{T}_N^U(x) + \sup \mathrm{I}_N^U + \sup\mathrm{F}_N^U(x) \ge 3.$ [44]

For convenience, the interval neutrosophic number (IVNN) ρ presented as $\rho = \langle [\inf T, \sup\mathrm{T}], [\inf \mathrm{I}, \sup \mathrm{I}], [\inf F, \sup\mathrm{F}] \rangle$.

Let's consider the concept of interval neutrosophic set used in practical problems of diagnosing diseases in cattle. The definition of these sets provides a tool for more accurate and reliable characterization of animal health conditions, making them useful in real-life clinical scenarios and veterinary medical issues.

The results of the intersection of two interval neutrosophic sets A and B is the set C, denoted as $C = A \cap B$. It contains elements that belong to both A and B. That is, true-membership, indefinite-membership, and false-membership membership in set C are related to membership in A and B as follows.

$$\inf T_C(x) = \min(\inf T_A(x), \inf T_B(x)),$$
$$\sup T_C(x) = \min(\sup T_A(x), \sup T_B(x)),$$
$$\inf I_C(x) = \max(\inf I_A(x), \inf I_B(x)),$$
$$\sup I_C(x) = \max(\sup I_A(x), \sup I_B(x)),$$
$$\inf F_C(x) = \max(\inf F_A(x), \inf F_B(x)),$$
$$\sup F_C(x) = \max(\sup F_A(x), \sup F_B(x)),$$

for everyone x in X [48]

$A \cap B$ is the largest interval neutrosophic set contained in both A в B.

Let U_N denote the neutrosophic union of two interval neutrosophic sets A и B. Then U_N has a function.

$U_N : N \times N \to N$ and U_N must satisfy at least the following four axiomatic requirements:

$U_N\left(A(x),\underline{0}\right)=A(x),$ for all x and X (boundary condition).

$B(x)\le C(x) implies U_N\left(A(x),B(x)\right)\le U_N\left(A(x),C(x)\right),$ for all x in X (monotone).

$U_N\left(A(x),B(x)\right)=U_N\left(B(x),A(x),B(x)\right),$ for all x in X (commutativity).

$U_N\left(A(x),U_N\left(B(x),C(x)\right)\right)=U_N\left(U_N\left(A(x),B(x),C(x)\right)\right),$ for all x in X associativity) [39].

Union of two interval neutrosophic sets A and B represents an interval neutrosophic set C, which is described through truth-belonging $C=A\cup B,$ degree of uncertainty-membership and falsity-membership in accordance with those of the sets A and B.

$$\inf T_C(x)=\max\left(\inf T_A(x),\inf T_B(x)\right),$$
$$\sup T_C(x)=\max\left(\sup T_A(x),\sup T_B(x)\right),$$
$$\inf I_C(x)=\min\left(\inf I_A(x),\inf I_B(x)\right),$$
$$\sup I_C(x)=\min\left(\sup I_A(x),\sup I_B(x)\right),$$
$$\inf F_C(x)=\min\left(\inf F_A(x),\inf F_B(x)\right),$$
$$\sup F_C(x)=\min\left(\sup F_A(x),\sup F_B(x)\right),$$

for all x in X [38]

The semantics of interval neutrosophical predicate calculus is aimed at the interpretation of correctly constructed formulas. In the framework of intervallic neutrosophical propositional logic, interpretation is the assignment of truth values to propositions using an ordered ternary component. Since first-order neutrosophical interval predicate logic uses variables, certain steps must be taken. To precisely define the interpretation of a well-formulated formula, this logic requires specifying two aspects: the domain of definition and the assignment of values to the constants and predicate symbols present in the formula. Below is a formal definition of the interpretation of a formula in the interval neutrosophical logic of first-order predicates [48-49].

$$INL(p)=\langle t(p),i(p),f(p)\rangle.$$

Let this assignment be provided by a certain interval neutrosophic fuzzy logic (INL) over a set of sentences such that P

$$INL(p)=\left\langle t(p),i(p),f(p)\right\rangle.$$

Therefore, the function $INL:P\rightarrow N$ gives the degrees of truth, uncertainty, and falsity of all propositions in P.

Table 1: Semantics of the four connectives in interval neutrosophic propositional logic

Connectives	Semantics
$INL(\neg p)$	$\left\langle f(p),1-i(p),t(p)\right\rangle$
$INL(p\wedge q)$	$\left\langle \min\left(t(p),t(q)\right),\max\left(i(p),i(q)\right),\max\left(f(p),f(q)\right)\right\rangle$
$INL(p\vee q)$	$\left\langle \max\left(t(p),t(q)\right),\min\left(i(p),i(q)\right),\min\left(f(p),f(q)\right)\right\rangle$
$INL(p\rightarrow q)$	$\left\langle \min\left(1,1-t(p)+t(q)\right),\max\left(0,i(q)-i(p)\right),\max\left(0,f(q)-f(p)\right)\right\rangle$

One practical application of interval neutrosophical logic is in the interval neutrosophical logic system (INLS). INLS is able to handle ambiguity in rules in a similar way to Type 2 fuzzy logic [47-48], while also being able to handle inconsistency in rules without the risk of simplification. Similar to classical fuzzy logic, INLS uses IF-THEN rules. The components of INLS include neutrosophics, neutrosophic inference, neutrosophic rule base, neutrosophic type reduction, and deneutrosophics. When given an input vector of $x=(x_1,...,x_n)$ data, where $x_1,...,x_n$ where each element is an input or neurosophical data set, INLS generates crisp output y.

Suppose that the neutrosophic rule base consists of M rules in which each rule has n antecedents and one consequence. Let k - the rule for constructing the interval neutrosophical fuzzy logic model be denoted by Sugeno R^k [51].

Let us assume that the base of neutrosophic rules is represented by rules M, where each rule contains n antecedents and one consequence. Let the k designation of the rule R^k be such that the construction of the interval neutrosophical fuzzy-logical Sugeno model is carried out as follows:

$$\bigcup_{p=1}^{k_j}\left(\bigcap_{k=1}^{n} x_i = A_i^k - w_{jp} \quad \text{with weight}\right) \to y_j = B^k = b_{k,0} + b_{k,1}x_1 + \ldots + b_{k,n}x_n + \\ + b_{k,n+1}x_1^2 + \ldots + b_{k,2n}x_n^2 + \ldots + b_{k,n+l-1}x_1^l + \ldots + b_{k,ln}x_n^l. \tag{5}$$

$A_{i,jp}^k$ is an interval neutrosophic set defined in X_i a sphere with a truth-membership function, $T_{A_i^k}(x_i)$, an uncertainty-membership function $I_{A_i^k}(x_i)$ falsity-membership function $F_{A_i^k}(x_i)$, where $T_{A_i^k}(x_i), I_{A_i^k}(x_i), F_{A_i^k}(x_i) \subseteq [0,1], 1 \le i \le n.$ B^k is an interval neutrosophic set defined in a space Y with a truth membership function $T_{B^k}(y)$, an uncertainty membership function $I_{B^k}(y)$ and a falsity membership function $F_{B^k}(y)$, , where $T_{B^k}(y), I_{B^k}(y), F_{B^k}(y) \subseteq [0,1].$ In a given x_1 is $\tilde{A}_2^k,...,$ and x_n is $\tilde{A}_n^k$, then y the $\tilde{B}^k$ consequence $\tilde{A}_i^k$ of the rule is an interval neutrosophic set defined in space X_i with a membership function to truth, $T_{\tilde{A}_i^k}(x_i)$ a membership function to uncertainty $I_{\tilde{A}_i^k}(x_i)$ and a membership function to falsity $F_{\tilde{A}_i^k}(x_i)$, where $T_{\tilde{A}_i^k}(x_i), I_{\tilde{A}_i^k}(x_i), F_{\tilde{A}_i^k}(x_i) \subseteq [0,1], 1 \le i \le n.$ $\tilde{B}^k$ an interval neutrosophic set defined in space Y with a membership function to truth $T_{\tilde{B}^k}(y)$, membership function of uncertainty $I_{\tilde{B}^k}(y)$ and membership function of falsity, $F_{\tilde{B}^k}(y)$ where we have a look at $a_i \le x_i \le b_i$ и $\alpha \le y \le \beta$. An unconditional neutrosophic judgment is expressed by the phrase: «Z has got C», where Z — variable that receives values z from the universal set U, a C — interval neutrosophic set defined on U representing a neutrosophic predicate. Each neutrosophic position p connected with $\langle t(p), i(p), f(p)\rangle$ c $t(p), i(p), f(p) \subseteq [0,1]$. In general, for any value of Z, $\langle t(p), i(p), f(p) = \langle T_C(z), I_C(z), F_C(z)\rangle$ [48-49].

For implication $p \to q$ the semantics is defined as follows:

$$\sup t_{p\to q} = \min\left(\sup t(p), \sup t(q)\right),$$

$$\inf t_{p\to q} = \min\left(\inf t(p), \inf t(q)\right),$$

$$\sup i_{p\to q}=\max\left(\sup i(p),\sup i(q)\right),$$
$$\inf i_{p\to q}=\max\left(\inf i(p),\inf i(q)\right),$$
$$\sup f_{p\to q}=\max\left(\sup f(p),\sup f(q)\right),$$
$$\inf f_{p\to q}=\max\left(\inf f(p),\inf f(q)\right),$$
$$\sup t_{p\wedge q}=\min\left(\sup t(p),\sup t(q)\right),$$
$$\inf t_{p\wedge q}=\min\left(\inf t(p),\inf t(q)\right),$$
$$\sup i_{p\wedge q}=\max\left(\sup i(p),\sup i(q)\right),$$
$$\inf i_{p\wedge q}=\max\left(\inf i(p),\inf i(q)\right),$$
$$\sup f_{p\wedge q}=\max\left(\sup f(p),\sup f(q)\right),$$
$$\inf f_{p\wedge q}=\max\left(\inf f(p),\inf f(q)\right),$$
$$\sup t_{p\vee q}=\max\left(\sup t(p),\sup t(q)\right),$$
$$\inf t_{p\vee q}=\max\left(\inf t(p),\inf t(q)\right),$$
$$\sup i_{p\vee q}=\min\left(\sup i(p),\sup i(q)\right),$$
$$\inf i_{p\vee q}=\min\left(\inf i(p),\inf i(q)\right),$$
$$\sup f_{p\vee q}=\min\left(\sup f(p),\sup f(q)\right),$$
$$\inf f_{p\vee q}=\min\left(\inf f(p),\inf f(q)\right),$$

where $t(p),i(p),f(p),t(q),i(q),f(q)\subseteq[0,1]$.

Let $X=X_1\times\ldots\times X_n$. Truth membership function, uncertainty membership function and membership function $T_{\tilde{B}^k}(y),I_{\tilde{B}^k}(y),F_{\tilde{B}^k}(y)$ falsity k. The rule can be represented using the definition of interval neutrosophic composition functions.

Neutrosophic number of L-R type: The quantities of truth, uncertainty and falsity are independent: The neutrosophic number of the L-R type is defined as $\tilde{A}_{Nue}=\left(p_1,p_2,\mathrm{p}_3;q_1,q_2,q_3;r_1,r_2,r_3\right)$ membership functions of the neutrosophic fuzzy truth set $\mathrm{T}_{\tilde{A}_{Neu}}\mu(x)$, uncertainty $\mathrm{I}_{\tilde{A}_{Neu}}\mu(x)$ and belonging to falsity $F_{\tilde{A}_{Nue}}\mu(x)$, which is defined as follows.

Gauss membership functions of a neutrosophic fuzzy set:

$$\mathrm{T}_{\tilde{A}_{Neu}}\mu(x)=\begin{cases} e^{\frac{-(x-p_1)^2}{(p_2-p_1)^2}} & \textit{когда}\ \mathrm{p}_1\le x\le p_2 \\ e^{\frac{-(p_3-x)^2}{(p_3-p_2)^2}} & \textit{когда}\ \mathrm{p}_2< x\le p_3 \end{cases}$$

$$I_{\tilde{A}_{Neu}}\mu(x)=\begin{cases} e^{\frac{-(q_2-x)^2}{(q_2-q_1)^2}} & когда\ q_1 \le x \le q_2 \\ e^{\frac{-(x-q_2)^2}{(q_3-q_2)^2}} & когда\ q_2 < x \le q_3 \end{cases}$$

$$F_{\tilde{A}_{Nue}}\mu(x)=\begin{cases} e^{\frac{-(r_2-x)^2}{(r_2-r_1)^2}} & когда\ r_1 \le x \le r_2 \\ e^{\frac{-(x-r_2)^2}{(r_3-r_2)^2}} & когда\ r_2 < x \le r_3 \end{cases}$$

Each of the features is closely related to diagnosis and clinical decisions. Target variables (presence or absence of disease) are highly correlated with the features. To reduce the amount of repeated data, data redundancy was avoided. The features can be measured or extracted from medical data. Measurement errors have little effect on the features.

These criteria ensured a balance between the accuracy of the model and practical applicability in diagnostics.

3. Results (examples / case studies related to the proposed work)

Diagnostics plays a key role in modern veterinary medicine. The development of interval neutrosophical fuzzy set methods for diagnosing cattle diseases can significantly improve the efficiency and accuracy of diagnosis. This process often uses parameters called disease traits. Let us give an example of diseases in cattle, such as osteodystrophy, secondary osteodystrophy, hypomicroelementosis and ketosis, each with 17 signs. However, for illustration, we will highlight the main 2 signs of cattle diseases.

According to accepted veterinary clinical practice, diagnostic results in cattle can be classified as follows:

y_1 - ketosis;

y_2 - osteodystrophy;

y_3 - secondary osteodystrophy;

y_4 - hypomicroelementosis

The listed types of diseases, such as osteodystrophy, ketosis, secondary osteodystrophy, hypomicroelementosis in cattle, are subject to diagnosis. When establishing diagnoses, the main parameters presented below are taken into account (possible values are indicated in parentheses, including) $x_1 - x_{17} \in \{0,1\}$) [52-55]. For osteodystrophy, ketosis, secondary osteodystrophy, hypomicroelementosis in cattle, the following main signs are taken into account when making diagnoses.

x_1 - Temperature ^{o}C;

x_2 - Pulse, per minute;

x_3 - Breathing, in one minute;

x_4 - Rumination, in two minutes;

x_5 - Number of red blood cells million/μl

x_6 - Hemoglobin, g/l by the method (Sali Hemometer);

x_7 - Total protein, g/l (by refractometry);

x_8 - Total calcium, mmol/l (Vigev. Karakashov method);

x_9 - Organic phosphorus mmol/l (Pulse method by V.F. Kromyslov, modified by L.A. Kudryatsev);

x_{10} - Glucose, mmol/l (color reaction with orthotoluidine);

x_{11} - Reserve alkali ( ) vol % (by I.P. Kondrakhin's method);

x_{12} - Copper mmol/l;

x_{13} - Cobalt mmol/l;

x_{14} - Manganese mmol/l;

x_{15} - Zinc mmol/l;

x_{16} - The number of ciliates in the rumen is 1000/ml;

x_{17} - State of scar fluid (Rameter) [44-46].

The task of diagnostic classification is to compare one of the solutions to each combination of parameter values $y_j\,(j=\overline{1,4})$.

For each feature, a membership function of a neutrosophic fuzzy set is constructed with the terms Extremely low level, Very low level, Low, Average, Average good, Good, Very good, Extremely good. As an example, we provide interval neutrosophic set of the feature - Cobalt mmol/l of diseases osteodystrophy, ketosis, hypomicroelementosis and secondary osteodystrophy of cattle:

Table 1

Interval neutrosophic sets of eight terms of the feature -Cobalt mmol/l

№		
1.	Extremely good:	$\left[(0.83, 0.85),(0.527, 0.544)(0.51, 0.544)\right],$
2.	Very good:	$\left[(0.765, 0.833),(0.544, 0.561)(0.544, 0.578)\right],$
3.	Good:	$\left[(0.714, 0.765),(0.544, 0.578)(0.578, 0.595)\right],$
4.	Average good:	$\left[(0.6799, 0.714),(0.578, 0.595)(0.595, 0.629)\right],$
5.	Average:	$\left[(0.646, 0.6799),(0.578, 0.612)(0.629, 0.633)\right],$

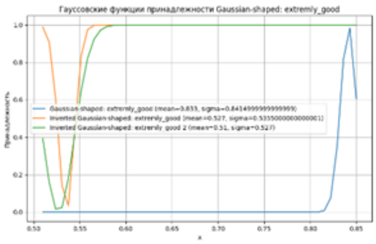
6.	Low:	$\left[(0.612, 0.646), (0.561, 0.595)(0.633, 0.6799)\right],$
7.	Very low level:	$\left[(0.527, 0.578), (0.544, 0.561)(0.731, 0.782)\right],$
8.	Extremely low level:	$\left[(0.51, 0.527), (0.527, 0.544)(0.782, 0.833)\right],$

Table 2

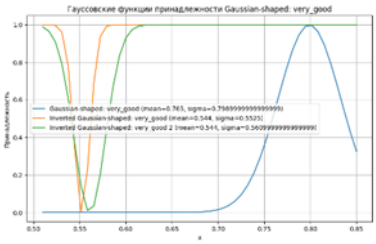
Graphs of the Gaussian membership function of a neutrosophic fuzzy set with terms

x_{13} - Cobalt mmol/l

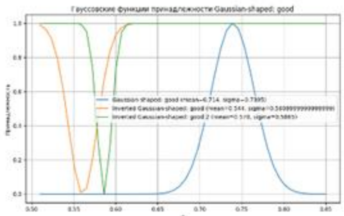
Extremely good



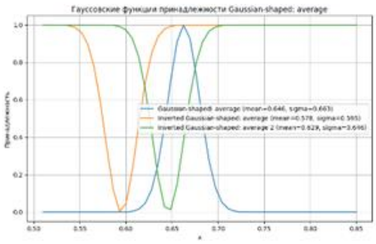
Very good



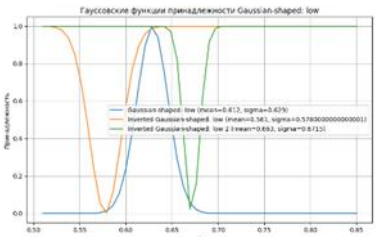
Good



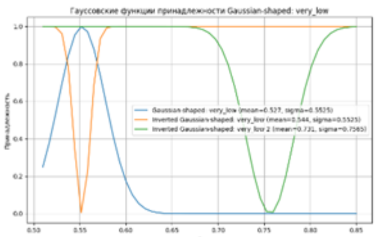
Average good



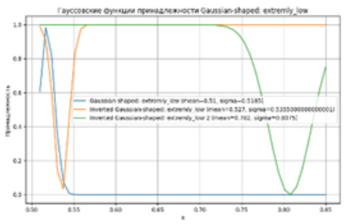
Average



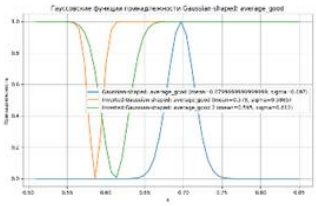
Low



Very low



Extremely low



The use of interval neutrosophic sets may represent a valuable method for disease modeling and diagnosis, as they are able to account for uncertainty and inconsistency in the provided data.

To introduce interval neutrosophic sets into the process of diagnosing cattle diseases, you can use set-theoretic operations, such as intersection, union and addition. This allows you to combine different parameters and assessments for more accurate analysis.

By applying interval neutrosophic fuzzy set methods to the diagnosis of cattle diseases, it is possible to create such sets for each of the 17 traits. Using interval neutrosophic set operations, an aggregated estimate for the diagnostic process can then be obtained. This approach allows us to take into account various aspects and relationships between parameters when assessing diagnostics.

The use of each set theory operation with interval neutrosophic set makes it possible to model various aspects and combine parameters when performing diagnostic evaluation.

To solve several examples, two signs of illness are used x_1 - Temperature ^oC and x_2 - Pulse, in one minute. We present several examples in Appendix A.

While Mamdani produces a fuzzy output that requires an additional defuzzification step, the Sugeno model uses crisp or linear functions for output. Sugeno is suitable for complex systems and real time because it is compact and requires less computational resources. Since Sugeno provides precise numerical values, while Mamdani provides fuzzy results, it is better suited for interpreting and understanding the results. The fast data processing due to the clear output values of the Sugeno model is especially important in clinical situations. For tasks such as disease diagnosis that require high speed and accuracy, the Sugeno model is the right choice.

Now we can give an algorithmic description of the interval neutrosophical fuzzy-logical model of Sugeno.

An algorithm for constructing a logical knowledge base of cattle is proposed, based on an interval neutrosophic set (Figure 1).

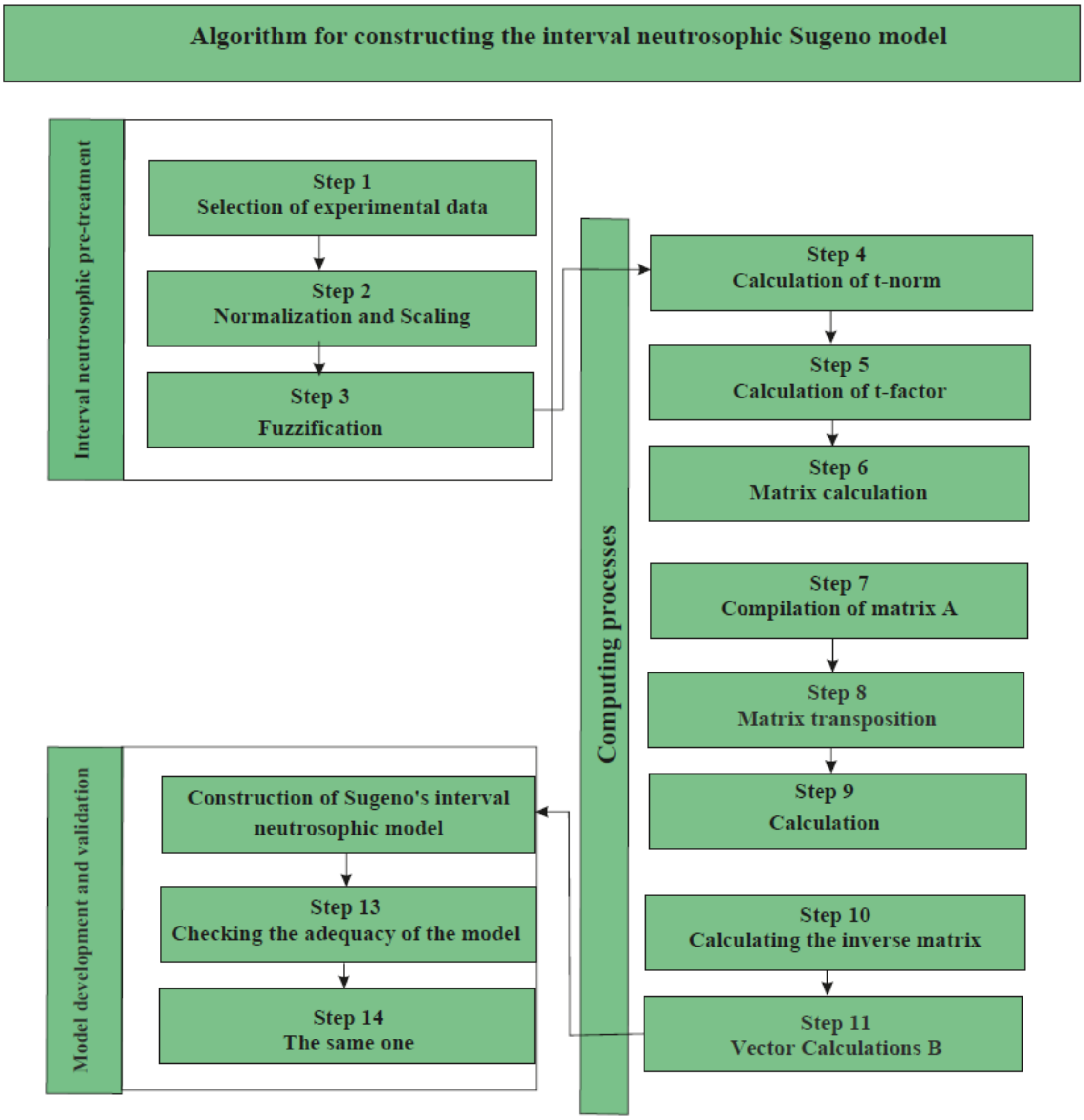
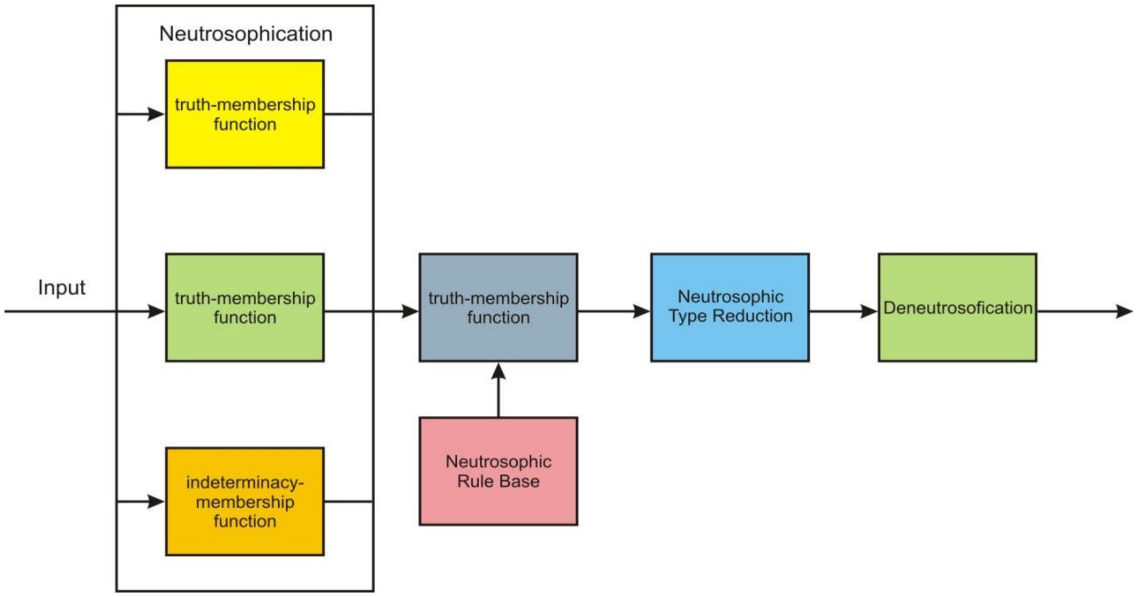


Figure 1 Algorithm for constructing the interval neutrosophic Sugeno model

Now we can give an algorithmic description of the interval neutrosophic-logical Sugeno model.

Step 1: Transition to Neutrosophy



Step 2: Neutrosophic set

Let G_i^k - be an interval neutrosophic input set representing the result of a neutrosophics i - input variable k - rule, then the goal of neutrosophics is to transform the input data into an interval neutrosophics set. Let us assume that this is G_i^k is an interval neutrosophic input set that reflects the result of applying neutrosophics i - to the input variable k - rule.

$$\sup T_{G_i^k}(x_i) = \sup_{x_i \in X_i} \min\left(\sup T_{\tilde{A}_i^k}(x_i), \sup T_{A_i^k}(x_i)\right), \tag{6}$$

$$\inf T_{G_i^k}(x_i) = \sup_{x_i \in X_i} \min\left(\inf T_{\tilde{A}_i^k}(x_i), \inf T_{A_i^k}(x_i)\right), \tag{7}$$

$$\sup I_{G_i^k}(x_i) = \sup_{x_i \in X_i} \max\left(\sup I_{\tilde{A}_i^k}(x_i), \sup I_{A_i^k}(x_i)\right), \tag{8}$$

$$\inf I_{G_i^k}(x_i) = \sup_{x_i \in X_i} \max\left(\inf I_{\tilde{A}_i^k}(x_i), \inf I_{A_i^k}(x_i)\right), \tag{9}$$

$$\sup F_{G_i^k}(x_i) = \inf_{x_i \in X_i} \max\left(\sup F_{\tilde{A}_i^k}(x_i), \sup F_{A_i^k}(x_i)\right), \tag{10}$$

$$\inf F_{G_i^k}(x_i) = \inf_{x_i \in X_i} \max\left(\inf F_{\tilde{A}_i^k}(x_i), \inf F_{A_i^k}(x_i)\right), \tag{11}$$

where $x_i \in X_i$

If x_i the input data is clear, then equations (6) – (11) are simplified to

$$\sup T_{G_i^k}(x_i) = \sup T_{A_i^k}(x_i),$$

$$\inf T_{G_i^k}(x_i) = \inf T_{A_i^k}(x_i),$$

$$\sup I_{G_i^k}(x_i) = \sup I_{A_i^k}(x_i),$$

$$\inf I_{G_i^k}(x_i) = \inf I_{A_i^k}(x_i),$$

$$\sup F_{G_i^k}(x_i) = \sup F_{A_i^k}(x_i),$$

$$\inf F_{G_i^k}(x_i) = \inf F_{A_i^k}(x_i),$$

where $x_i \in X_i$

Step 3: Neutrosophic Inference

The core of the interval neutrosophic set is the neutrosophic inference.

The essence of the interval neutrosophic set is the neutrosophic inference.

Suppose that we have the k-e rule. Let G^k be the interval neutrosophic set, which is the result of the input operation for the k-th rule then

The essence of the interval neutrosophic set is the neutrosophic inference.

$$\sup T_{G_i^k}(x) = \sup_{x \in X} \min\left(\sup T_{\tilde{A}_1^k}(x_1), \sup T_{A_1^k}(x_i), \ldots, \sup T_{\tilde{A}_n^k}(x_n), \sup T_{A_n^k}(x_n)\right),$$

$$\inf T_{G^k}(x) = \sup_{x \in X} \min\left(\inf T_{\tilde{A}_1^k}(x_1), \inf T_{A_1^k}(x_1), \ldots \inf T_{\tilde{A}_n^k}(x_n), \inf T_{A_n^k}(x_n)\right),$$

$$\sup I_{G_i^k}(x) = \sup_{x \in X} \max\left(\sup I_{\tilde{A}_1^k}(x_1), \sup I_{A_1^k}(x_i), \ldots, \sup I_{\tilde{A}_n^k}(x_n), \sup I_{A_n^k}(x_n)\right),$$

$$\inf I_{G^k}(x) = \sup_{x \in X} \max\left(\inf I_{\tilde{A}_1^k}(x_1), \inf I_{A_1^k}(x_1), \ldots \inf I_{\tilde{A}_n^k}(x_n), \inf I_{A_n^k}(x_n)\right),$$

$$\sup F_{G_i^k}(x) = \inf_{x \in X} \max\left(\sup F_{\tilde{A}_1^k}(x_1), \sup F_{A_1^k}(x_i), \ldots, \sup F_{\tilde{A}_n^k}(x_n), \sup F_{A_n^k}(x_n)\right),$$

$$\inf F_{G^k}(x) = \inf_{x \in X} \max\left(\inf F_{\tilde{A}_1^k}(x_1), \inf F_{A_1^k}(x_1), \ldots \inf F_{\tilde{A}_n^k}(x_n), \inf F_{A_n^k}(x_n)\right),$$

where $x_i \in X_i$

It is possible to repeat the result of the neutrosophic inference

$$\sup T_{\tilde{B}^k}(y) = \min\left(\sup T_{G_1^k}(x), \sup T_{B^k}(y)\right),$$

$$\inf T_{\tilde{B}^k}(y) = \min\left(\inf T_{G^k}(x), \inf T_{B^k}(y)\right),$$

$$\sup I_{\tilde{B}^k}(y) = \max\left(\sup I_{G^k}(x), \sup I_{B^k}(y)\right),$$

$$\inf I_{\tilde{B}^k}(y) = \max\left(\inf I_{G^k}(x), \inf I_{B^k}(y)\right),$$

$$\sup F_{\tilde{B}^k}(y) = \max\left(\sup F_{G_1^k}(x), \sup F_{B^k}(y)\right),$$

$$\inf F_{\tilde{B}^k}(y) = \max\left(\inf F_{G^k}(x), \inf F_{B^k}(y)\right),$$

where $x \in X, y \in Y$.

Step 4: Neurosophical type reduction

After the neutrosophical derivation we obtain the interval neutrosophical set $\tilde{B}$ With $T_{\tilde{B}}(y), I_{\tilde{B}}(y), F_{\tilde{B}}(y), \subseteq [0,1]$. We then perform neurosophical reduction to convert each interval into a single number. There are several methods for doing this, and in this case we present one of them:

$$T'_{\tilde{B}}(y) = \left(\inf T_{\tilde{B}}(y) + \sup T_{\tilde{B}}(y)\right)/2,$$
$$I'_{\tilde{B}}(y) = \left(\inf I_{\tilde{B}}(y) + \sup I_{\tilde{B}}(y)\right)/2,$$
$$F'_{\tilde{B}}(y) = \left(\inf F_{\tilde{B}}(y) + \sup F_{\tilde{B}}(y)\right)/2,$$

where $y \in Y$.

So, after carrying out the neurosophical reduction, we obtain the usual neutrosophic set (neutrosophic set of the first type) $\tilde{B}$. After this, a deneutrosophy procedure is required to obtain a clear result.

Step 5: Deneutrosophy

The goal of deneutrosophics is to transform the ordinary neutrosophic set (neutrosophic set of the first type), obtained after the reduction of the neutrosophic type, into a single real number representing the actual result. Similar to the defuzzification process [56], there are many methods of deneutrosophics , and each of them can be applied according to specific applications. Here we look at one method that involves two steps in the process of deneutrosophics .

Step 5.1: Synthesis: This is the process of converting ordinary neutrosophic set (neutrosophic sets of type 1) $\tilde{B}$ in fuzzy set $\tilde{B}$. It can be expressed using the following function:

$$f\left(T_{\tilde{B}}^{'}(y), I_{\tilde{B}}^{'}(y), F_{\tilde{B}}^{'}(y)\right):[0,1]\times[0,1]\times[0,1]\to[0,1],$$

$$T_{\bar{B}}(y) = a * T_{\tilde{B}}^{'}(y) + b*\left(1 - F_{\tilde{B}}^{'}(y)\right) + c * I_{\tilde{B}}^{'}(y)/2 + d*\left(1 - I_{\tilde{B}}^{'}(y)/2\right),$$

where $0 \le a,b,c,d \le 1, a+b+c+d=1.$

It is necessary to find such values of the rule conclusion coefficients $B=(b_{1,0}+b_{2,0}\dots b_{m,0}+b_{1,1}+b_{2,1}\dots\dots b_{m,1}\dots b_{1,n}, b_{2,n}\dots\dots b_{m,n})^T$ which provide a minimum quadratic discrepancy:

$$\sum_{r=\overline{1,M}} \left(y_r - y_r^f\right)^2 \to \min, \tag{12}$$

where y_r^f - output of the input data in the r -sampling row (X_r) in the fuzzy knowledge base - b - parameter. The input vector $X_r = (x_{r,1}, x_{r,2}, \dots, x_{r,n})$ corresponds to the following fuzzy output result

$$y_r^f = \frac{\sum_{j=\overline{1,m}} \mu d_j(X_r) d_j}{\sum_{j=\overline{1,m}} \mu d_j(X_r)}, \quad dn\left(T_{\bar{B}}(y)\right) = \frac{\int_\alpha^\beta T_{\bar{B}}(y)\, y dy}{\int_\alpha^\beta T_{\bar{B}} dy},$$

$$dn\left(T_{B_r}(y_j)\right) = \frac{\sum_{j=1}^m T_{B_r}(y_j) y_j}{\sum_{j=1}^m T_{B_r}(y_j)}, \; j=\overline{1,m}, \; r=\overline{1,n},$$

$$\beta_{j,r} = \frac{T_{B_r}(y_j)}{\sum_{j=1}^m T_{B_r}(y_j)}$$

We denote by the relative degree of fulfillment of the conclusion of the jth rule for the input vector X_r. Then (5) can be rewritten as:

$$y_r^f = \sum_{j=\overline{1,m}} \beta_{r,j} \cdot d_j = \sum_{j=\overline{1,m}} \beta_{r,j} \cdot b_{j,0} + \beta_{r,j} \cdot b_{j,1} \cdot x_{r,1} + \beta_{r,j} \cdot b_{j,2} \cdot x_{r,2} + \dots + \beta_{r,j} \cdot b_{j,n} \cdot x_{r,n}.$$

Let us introduce the following notation:

$$y_r^f = (y_1^f . y_2^f ... y_M^f)^T,$$

$$Y = (y_1 . y_2 ... y_M)^T,$$

$$A = \begin{bmatrix} \beta_{1,1}, \dots, \beta_{1,m}; X_{1,1}\ \beta_{1,1}, \dots, X_{1,1}\ \beta_{1,m}, \dots, X_{1,n}\ \beta_{1,1}, \dots, X_{1,n}\ \beta_{1,m} \\ \beta_{M,1}, \dots, \beta_{M,m}; X_{M,1}\beta_{1,1}, \dots, X_{M,1}\ \beta_{1,m}, \dots, X_{M,n}\beta_{M,1}, \dots, X_{M,n}\beta_{M,m} \end{bmatrix}.$$

Then problem (12) in matrix form is stated as follows: find the vector B so that:

$$y_r^f = (y_1^f . y_2^f ... y_M^f)^T,$$

$$Y = (y_1 . y_2 ... y_M)^T,$$

$$E = (Y - Y^f)^T (Y - Y^f) \to \min,$$

where

$$Y^f = AB.$$

The minimum value of the quadratic residual E is achieved at $Y^f = Y$, which corresponds to the solution of the equation $Y = AB$. For real problems, the number of adjustable parameters is less than the size of the data sample $m(n+1) < M$, so the equation $Y = AB$ has a solution $B = (A^T A)^{-1} A^T Y$.

Step 6: End

Based on the developed algorithm, an interval neutrosophic fuzzy logical model of Sugeno was built for diagnosing cattle diseases using the main 17 signs. To assess the linguistic values of the input parameters, quantifiers were used: L - low level, B - high level, S - average level, NS - low average level, BC - high average level. The resulting fuzzy logic model is intended for more effective diagnosis of diseases in cattle. Interval neutorsophic fuzzy logical model for diagnosing cattle diseases.

Linguistic variables. Table 3

No.	Linguistic Variables	Interval - digits neutrosophic sets
1.	High	$\langle [0.75;0.1],[0.05;0.15],[0.1;0.2] \rangle$
2.	High Average	$\langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle$
3.	Average	$\langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle$
4.	Low Medium	$\langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle$
5.	Low	$\langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle$

If $x_1 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge x_2 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge$

$x_3 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge x_4 = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$

$x_5 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_6 = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$

$x_8 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge x_9 = \langle [0.75;0.1],[0.05;0.15],[0.1;0.2] \rangle \wedge$

$x_{10} = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge x_{11} = \langle [0.75;0.1],[0.05;0.15],[0.1;0.2] \rangle \wedge$

$x_{12} = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge x_{13} = \langle [0.75;0.1],[0.05;0.15],[0.1;0.2] \wedge$

$x_{14} = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge x_{15} = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25]$

$x_{16} = \langle [0.75;0.1],[0.05;0.15],[0.1;0.2] \rangle \wedge x_{17} = \langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle \vee$

$x_1 = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge x_2 = \langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle \wedge$

$x_3 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_4 = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$

$x_5 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_6 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge$

$x_7 = \langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle \wedge x_8 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge$

$x_9 = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge x_{10} = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge$

$x_{11} = \langle [0.75;0.1],[0.05;0.15],[0.1;0.2] \rangle \wedge x_{12} = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$

$x_{13} = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge x_{14} = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge$

$x_{15} = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge x_{16} = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge$

$x_{17} = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle$

Then

$$y_1 = -1{,}36 + 0{,}0010x_1 - 0{,}0021x_2 - 0{,}020x_3 + 0{,}029x_4 - 0{,}0048x_5 + 0{,}0058x_6 - 0{,}0001x_7 - 0{,}015x_8 - 0{,}0070x_9 + 0{,}0005x_{10} + 0{,}041x_{11} + 0{,}0004x_{12} + 0{,}0004x_{13} - +1{,}60x_{14} - 5{,}155x_{15} - 0{,}0006x_{16} - 0{,}0005x_{17}$$

If $x_1 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_2 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle$

$\wedge\ x_3 = \langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle \wedge$

$x_4 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge x_5 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge$

$x_6 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge x_7 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge$

$x_8 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_9 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge$

$x_{10} = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_{11} = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge$

$x_{12} = \langle [0.75;0.1],[0.05;0.15],[0.1;0.2] \rangle \wedge x_{13} = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge$

$x_{14} = \langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle \wedge x_{15} = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$

$x_{16} = \langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle \wedge x_{17} = \langle [0.75;0.1],[0.05;0.15],[0.1;0.2] \rangle \vee$

$$x_1 = \langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle \wedge x_2 = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$$
$$x_3 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_4 = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$$
$$x_5 = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_6 = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$$
$$x_7 = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge x_8 = \langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle \wedge$$
$$x_9 = \langle [0.75;0.1],[0.05;0.15],[0.1;0.2] \rangle \wedge x_{10} = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge$$
$$x_{11} = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_{12} = \langle [0;0.2],[0.05;0.15],[0.65;0.95] \rangle \wedge$$
$$x_{13} = \langle [0.4;0.6],[0.2;0.3],[0.25;0.45] \rangle \wedge x_{14} = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$$
$$x_{15} = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle \wedge x_{16} = \langle [0.05;0.4],[0.1;0.25],[0.45;0.8] \rangle \wedge$$
$$x_{16} = \langle [0.6;0.75],[0.1;0.2],[0.2;0.25] \rangle$$

Then

$$y_2 = 2,695 - 0,0014x_1 + 0,0029x_2 + 0,00089x_3 - 0,0023x_4 + 0,0047x_5 - 0,0046x_6 - 6,6304x_7 + 0,001x_8 + 0,0071x_9 + 0,00062x_{10} - 0,0039x_{11} - 0,0004x_{12} - 0,0015x_{13} - +0,00020x_{14} + 0,00068x_{15} + 0,00079x_{16} - 0,0001x_{17}$$

The presented methodology for constructing an interval neutrosophical fuzzy-logical Sugeno model for solving problems of diagnosing cattle diseases is a modern specialization in the field of artificial intelligence. Its goal is to develop methods that bring computational solutions closer to those used by humans in various fields of knowledge. For each variable, within the framework of this methodology, interval neutrosophical fuzzy sets are created that describe this variable. For each interval neutrosophical fuzzy set, a membership function is also constructed. Rules are then defined that relate the output and input variables to the corresponding interval neutrosophical fuzzy sets.

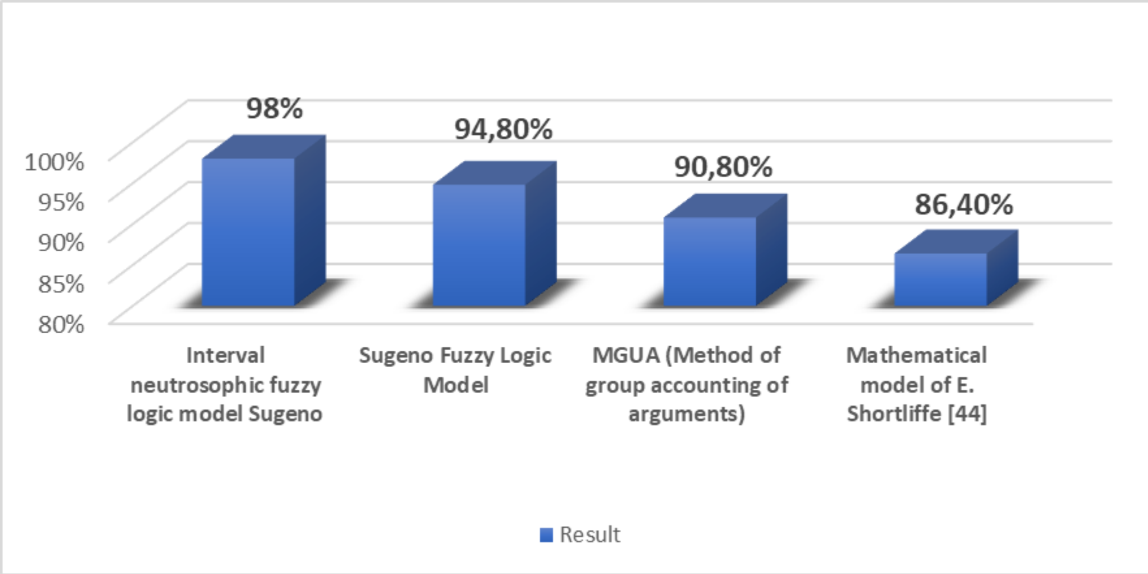
An interval fuzzy logic inference algorithm was created and the relationship between the parameters was analyzed. In order to fully take into account the fuzzy information, our task was to develop an interval neutrosophic fuzzy algorithm that would use fuzzy arithmetic in fuzzy logic inference. This direction is aimed at minimizing the loss of information, including uncertainties, in the framework of a computational experiment.

During the classification, errors in the range from 2 to 14% were detected. However, after applying the interval neutrosophic fuzzy-logical Sugeno model, the error level was significantly reduced. Table 2 presents the results obtained at various levels using the proposed interval neutrosophic fuzzy-logical Sugeno model, and also compares them.

The presented error rates are consistent with modern methods. Increasing the number of rules in the model, using adaptive machine learning algorithms, and improving data quality can lead to a reduction in errors.

The interval neutrosophic Sugeno fuzzy-logical model was developed and compared with the results obtained using the Sugeno fuzzy-logical model, the group argument accounting method and the mathematical model of E. Shortliffe (diagram 1).

Comparative result. Diagram 1



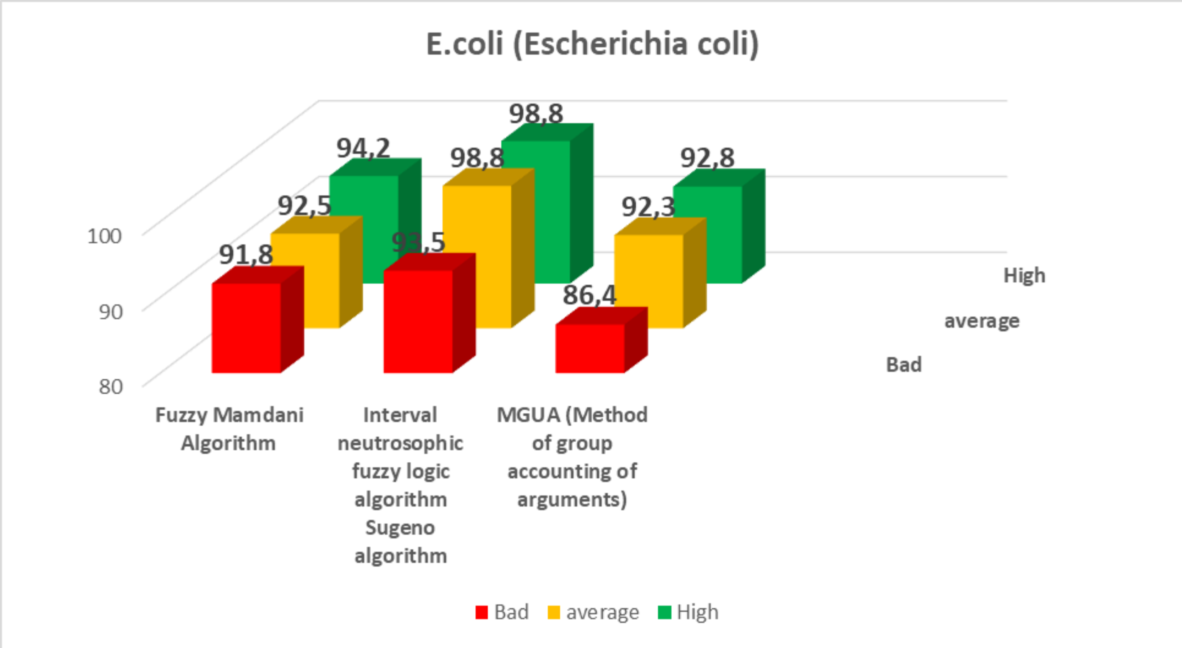
To perform the comparative analysis, well-known model problems available at the following web address were selected: [http://www.ics.uci.edu/~mlearn/databases/.] Among them, problems such as Ecoli Data Set, Hepatitis C Virus (HCV) for Egyptian patients, and Breast Cancer Coimbra were included. Table 4 shows the characteristics of these problems and the problem considered in this study.

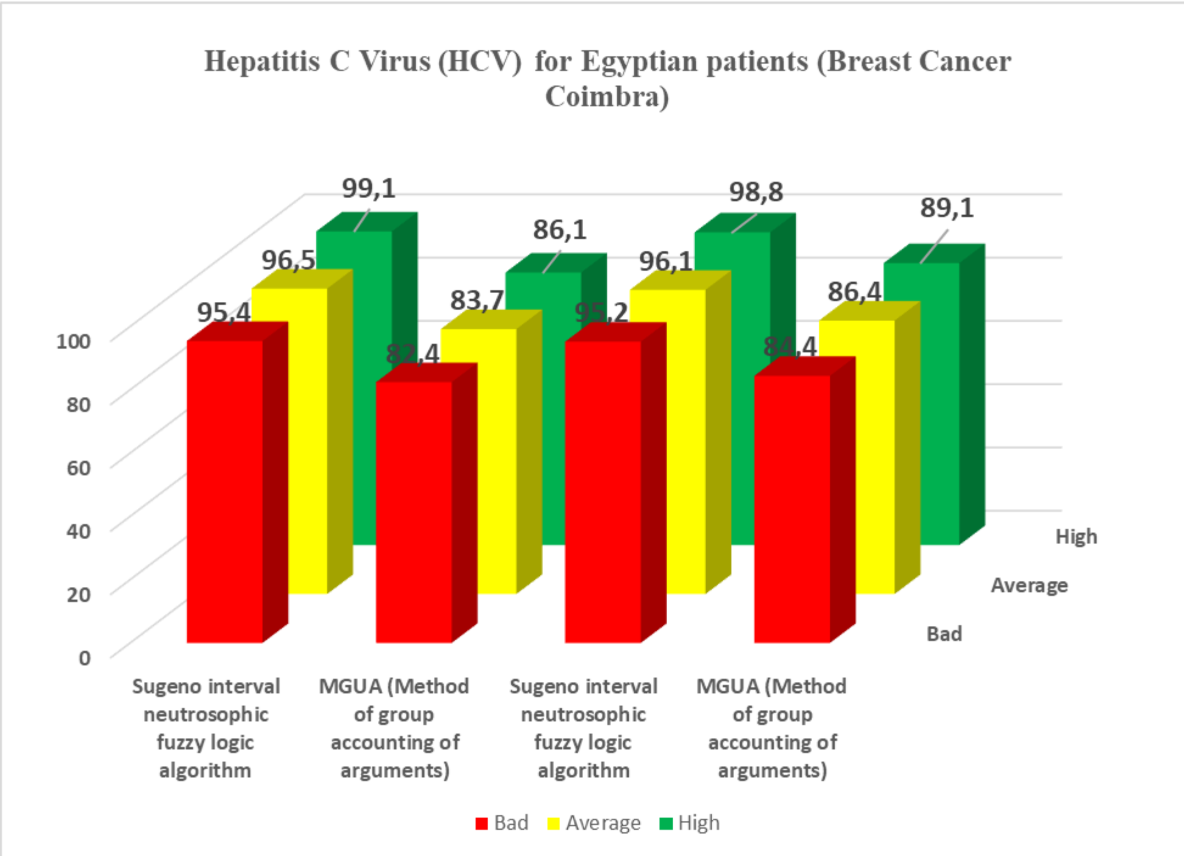
Parameters of model problems and the proposed model. Table 4

Task name	Number of classes	Number of features	Number of objects
E. coli (Escherichia coli)	7	8	336
Hepatitis C Virus (HCV) for Egyptian patients	4	19	1385
Breast Cancer Coimbra	2	10	116
Cattle	4	17	100

Figure 2 presents the results of solving several model problems using various known and proposed algorithms for comparative analysis. To demonstrate the effectiveness of our proposed model, we compared it with algorithms applied to the E.coli, Hepatitis C Virus (HCV) in Egyptian patients, and Breast Cancer in Coimbra problems [http://www.ics.uci.edu/~mlearn/databases/], with the results presented in Figures 2 and 3.

Comparison of the results of the proposed and existing algorithms. Diagram 2.





Recognition of bacterial types. HCV (Hepatitis C Virus): Diagnosis of hepatitis C in Egyptian patients. Breast Cancer Coimbra: Diagnosis of breast cancer based on biochemical analysis. The proposed model is used for diagnosis of cattle diseases. These tasks allow us to evaluate the universality of the model, since they differ in the number of classes, features and objects.

Sugeno interval neutrosophic fuzzy logic model, classical Sugeno model, group GMDH method and E. Shortliffe mathematical model were used for each task. The following parameters were used to evaluate the performance of the models: Accuracy: the percentage of objects that were correctly classified. F1-measure means that the accuracy and recall are at the average level. Root Mean Square Error (RMSE) is the difference between the actual and expected values. Overall Skill: The metrics were compared on both the training and test sets.

The data sets were divided into test and training samples in a ratio of 70:30. The same approaches to data preprocessing and standardization were used at the training stage. To exclude random factors, k-fold cross-testing was carried out, with k = 10. Through interval values of membership functions, the Sugeno interval neutrosophic model took into account the uncertainty and inconsistency of data. The classical Sugeno model had transparent values of membership functions. Taking into account nonlinear dependencies, GMDH selected the most important characteristics. The Shortliffe model uses a probabilistic approach to decision-making with medical knowledge.

Each model was used in the test set, and the results were compared with the reference class labels. For each model and task, accuracy, F-measure, and errors were calculated. In contrast to the classical Sugeno and GMDH models, the interval neutrosophic Sugeno model showed higher F-measure values and lower root mean square error (RMSE). The interval model demonstrated significant improvement in accuracy on high-uncertainty tasks such as HCV. For the cattle diagnostic task, the accuracy was 92%, F-measure was 0.89, and RMSE was 0.11. This gives better results than other methods. The interval model handled the test data better, indicating that it is robust to overfitting. The ability to account for uncertainty is an advantage of the interval neutrosophic model; it allows for better classification in problems with noisy and heterogeneous data. Although the classical Sugeno model works well, it is not as accurate under high uncertainty. Shortliffe and GMDH work well in problems with well-structured data, but are less adaptable to inconsistency.

Including a case study or practical example would greatly enhance the practical value. An example would be a diagnostic task in medical or veterinary practice similar to the tasks considered in the study: Diagnosis of cattle diseases on farms, the use of biochemical tests to assess the risk of developing cardiovascular diseases and the classification of infectious diseases. This study used available datasets from the UCI Machine Learning Repository for E. Coli or breast cancer tasks.

The novelty of the proposed approach is that it uses interval neutrosophic logic for diagnosing cattle diseases, which allows for inconsistency and uncertainty in data. Interval neutrosophic logic effectively handles gaps and noisy data typical of veterinary examinations in the field. This distinguishes it from traditional methods such as statistical models or Mamdani fuzzy logic. Promotes more accurate and reliable diagnostics. The proposed method reduces the classification error to 3-13%. This is higher than the results of other methods used in veterinary practice. Provides the ability to adapt to resource-limited conditions. The model is useful in agricultural areas where there are no full-fledged laboratory studies, and it allows for diagnostics with a small amount of data. Promotes the decision-making process. The method not only diagnoses diseases, but also reports the degree of uncertainty of the diagnosis, which helps the veterinarian decide whether further studies are needed. promotes modern methods of diagnostics of dogs. The integration of interval neutrosophic logic provides new opportunities for data processing under uncertainty. This increases the level of diagnostics compared to existing methods. The proposed method solves the main problems of animal diagnostics, increasing its efficiency and reliability, especially in complex and resource-intensive situations.

To develop and test the model, standard cattle diagnostic methods were used to collect data from different farming areas. The study included collecting information on clinical symptoms, animal disease history, and test results. The data included primary data from farmers and veterinarians, as well as secondary data from scientific publications and databases such as the UCI Machine Learning Repository. Disease symptoms in cattle are not considered as individual signs. Uncertainty in data, such as missing information or inconsistent values, is considered normal. To ensure compatibility with the model, all collected data were first normalized. The test sample was thirty percent, and the training sample was seventy percent. Cross-validation, also known as k-cell cross-validation, was used to test the stability of the model. Only data that had enough features to determine a diagnosis were included in the analysis. Interval neurosophic logic methods were used to replace missing values.

In the considered problems, our proposed interval neutrosophic Sugeno logic model demonstrated higher efficiency compared to other methods, providing better results.

Need and limitations of the study

Need for research: Current methods of diagnostics of cattle diseases are often ineffective due to the complexity of working with data containing uncertainty, inconsistency and insufficiency. Early diagnostics of diseases such as osteodystrophy, ketosis and hypomicroelementosis is critical to minimizing losses in livestock productivity and increasing the economic stability of farms. However, current approaches such as classical fuzzy logic or statistical models do not provide the required level of accuracy in real veterinary practice.

Limitations of the work: The proposed method, despite its effectiveness, has certain limitations. It requires high-quality data for training the model and may encounter problems when working with a small amount of data. In addition, the use of interval neurosophic logic requires additional computing resources, which can be difficult in the conditions of farms with a limited technical base. Correct adjustment of the model parameters is also important, which requires a certain level of qualification of specialists.

Impact of the study: The developed interval neutrosophic Sugeno model provides veterinarians with a new tool for diagnosing cattle diseases, allowing for uncertainty and inconsistency in data. This improves the accuracy of predictions and reduces the percentage of diagnostic errors to 3-13%. The work contributes to the introduction of modern artificial intelligence methods into veterinary practice, improving the quality of diagnostics and reducing economic losses in animal husbandry. In addition, the proposed methodology can be adapted to diagnose other diseases and animal species, which opens up prospects for further research and development.

Comparative study

To evaluate the effectiveness of the proposed interval neutrosophic Sugeno model, a comparative analysis was performed with other well-known methods: the classical Sugeno model , the group GMDH method, and the Shortliffe mathematical model. Accuracy, F1-measure, and root mean square error (RMSE) were used as comparison criteria. The proposed model showed an accuracy of 92%, which is 5-10% higher than the classical Sugeno model and the Shortliffe method. The GMDH model showed lower accuracy (about 85%), which indicates its limited ability to take into account data uncertainty. The F1-measure value of the proposed model was 0.89, which indicates a balance between accuracy and recall. This is higher than that of the classical Sugeno model (0.82) and GMDH (0.78). The proposed model had RMSE of 0.11, which is significantly less than other methods (for example, 0.18 for the classical Sugeno model and 0.21 for Shortliffe).

The advantage of the proposed model is its ability to take into account the uncertainty and inconsistency of data due to the use of interval neutrosophic sets. The classical Sugeno model and the Shortliffe method demonstrated good results when working with deterministic data, but their efficiency decreased in the presence of heterogeneity or inconsistency in the data. The GMDH model showed good results in the analysis of linear dependencies, but did not cope with the consideration of complex nonlinear relationships between features. These results confirm that the proposed model provides higher accuracy and reliability of diagnostics compared to existing approaches. This makes it a promising tool for use in veterinary practice.

Sensitivity analysis

Sugeno interval neutrosophic model, a sensitivity analysis was performed to assess the effect of input parameter changes on the accuracy and stability of the model. Experiments were conducted with artificial changes in the values of key diagnostic features, such as temperature, pulse, and hemoglobin levels. The effect of changes was assessed by gradually increasing and decreasing feature values by ±10%, ±20%, and ±30% of their initial values. Exclusion of individual features was also tested to determine their effect on the overall performance of the model. The model remained stable when the diagnostic feature values varied within ±20%. With a change of ±30%, a decrease in diagnostic accuracy by 3–5% was observed, indicating the sensitivity of the model to significant data fluctuations. Removal of features such as “copper level” and “rumination” had virtually no effect on the results. However, exclusion of key parameters such as “hemoglobin” and “glucose” led to a decrease in accuracy by 7–10%, emphasizing their importance for the model.

The model demonstrates high stability to moderate changes in input data, which makes it reliable in real veterinary practice, where measurement errors are possible. Sensitivity to key diagnostic parameters emphasizes the need for careful selection and quality control of input data. To improve the model's stability to significant data changes, it is recommended to use normalization methods and an expansion of the training data set. Sensitivity analysis can be further deepened by using factor analysis methods to identify the most important parameters.

1. Discussion

In the field of veterinary diagnostics, the use of interval neutrosophic logic opens up new possibilities for increasing the accuracy and reliability of diagnostic processes.

The processing of animal symptom data can be automated using the interval neutrosophic model, which reduces diagnostic time and reduces dependence on the human factor. This is especially important for large enterprises that require processing large amounts of information. The model takes into account the uncertainty and inconsistency of data that are often encountered in veterinary practice, unlike traditional methods. This makes it useful in cases where information about the animal's condition is insufficient or ambiguous. The method can be used as a diagnostic module in existing farm management information systems. For example, the model can be used in animal health monitoring systems that collect data from sensors measuring temperature, pulse, and activity.

Veterinarians can quantify the truth, falsity, and uncertainty of diagnoses using interval neutrophic logic. This facilitates decision making, especially in complex cases with overlapping symptoms. The proposed strategy is easily adaptable to new data and can be used to train less experienced veterinarians. The gradual accumulation of information will allow the models to be refined, making diagnostics more accurate and tailored. By reducing errors and increasing the efficiency of veterinary procedures, the implementation of this model reduces diagnostic costs. This is especially important for farmers with limited resources. Using the proposed method in veterinary practice, it is possible to significantly improve the diagnosis and management of cattle health. This can lead to improved animal health and economic stability of farms.

Although the proposed interval neutrosophic logic has been shown to be effective in diagnosing cattle diseases, there are several limitations that should be considered. The quality and volume of the collected data affect the model. This may affect the accuracy of the results if the data is incomplete, unreliable, or unbalanced (e.g., a predominance of one type of diagnosis). The parameters of the interval neutrosophic logic must be carefully tuned, which can be complex and require significant computational resources, so that the model can work effectively. Despite the high accuracy, the results of the interval neutrosophic logic-based models can be difficult for people without experience in artificial intelligence, so veterinarians should receive additional explanations. Calculations with large amounts of data and high levels of uncertainty may take longer than is acceptable in real time. This makes it impossible to apply the model to large farms with many animals. Implementation of the method may require training technicians and veterinarians to operate the system, which may require more time and resources. The model was developed for diagnosing specific cattle diseases. If applied to other animals or diseases, it may require significant modifications. To use the method, it is necessary to have the appropriate computing infrastructure, which may be a problem for small or remote farms.

Although these limitations do not detract from the advantages of the proposed methodology, they highlight the need for further research and optimization of the model to improve its accessibility and effectiveness in the real world.

In this study, the Sugeno interval neutrosophic model for diagnostics of cattle diseases is proposed and analyzed. The obtained results confirm the effectiveness of this approach in comparison with existing methods, including the classical Sugeno model, the group argument accounting method, and the Shortliffe mathematical model. The main advantage of the proposed model is its ability to take into account the uncertainty and inconsistency of data, which is typical for veterinary diagnostics. The use of the Sugeno interval neutrosophic model opens up new opportunities for automation and improving the accuracy of diagnostic processes in veterinary medicine. Integration of the model into animal health monitoring systems will significantly reduce the diagnostic time and reduce dependence on the human factor. This is especially important for large farms that require processing large amounts of data. The model also provides veterinarians with additional information on the degree of diagnostic uncertainty, which facilitates decision-making in complex cases.

The proposed interval neutrosophic Sugeno model has significant potential for implementation in veterinary practice. Further development of this direction will improve the accuracy of diagnostics and improve animal health management in real farm conditions. The main advantage of the model is its ability to take into account plausibility, falsity and uncertainty simultaneously, which is especially important in conditions of insufficient or heterogeneous data. This allows for more accurate forecasts and informed diagnostic decisions. However, the analysis also revealed certain limitations. For example, the computational complexity of the model increases with the number of rules and the volume of data, which may limit its use in farms with a limited technical base. In addition, the development of the model requires high-quality data preprocessing and the availability of qualified specialists to adjust the parameters.

The obtained results show the potential of the proposed model for integration into animal health monitoring systems. It can be used both in individual diagnostics and in complex information systems for veterinary practice.

2. Conclusion.

Although the proposed interval neutrosophic logic has been shown to be effective in diagnosing cattle diseases, there are several limitations that should be considered. The quality and volume of data collected impact the model. This may affect the accuracy of the results if the data is incomplete, unreliable, or unbalanced (e.g., a predominance of one type of diagnosis). The parameters of the interval neutrosophic logic must be carefully tuned, which can be complex and computationally intensive, for the model to work effectively. Despite the high accuracy, the results of models based on interval neutrosophic logic can be complex for people without experience in artificial intelligence, so veterinarians should receive additional explanations. Calculations with large amounts of data and high levels of uncertainty can take longer than is acceptable in real time. This makes it impossible to apply the model to large farms with many animals. Implementation of the method may require training of technicians and veterinarians to work with the system, which may require more time and resources. The model was developed to diagnose certain diseases of cattle. If applied to other animals or diseases, it may require significant modifications. To use the method, it is necessary to have the appropriate computing infrastructure, which may be a problem for small or remote farms.

Although these limitations do not detract from the benefits of the proposed methodology, they highlight the need for further research and optimization of the model to improve its accessibility and effectiveness in the real world.

In the course of the study on the use of interval neutrosophic fuzzy set and interval neutrosophic fuzzy logic methods for diagnosing cattle diseases, the following key results were obtained: A review was conducted of analytical methods in the field of soft computing, neutrosophic set, interval neutrosophic set and interval neutrosophic fuzzy logic methods used to solve classification problems. The analysis shows that the use of these methods in the diagnosis of cattle diseases leads to obtaining effective results. The methods of interval neutrosophic set were applied to the clinical signs of cattle diseases in order to take into account various aspects and relationships between parameters when conducting a diagnostic assessment. This approach helps to increase the reliability of information obtained from informative features. During the analysis, an algorithm of interval neutrosophic fuzzy logic was developed based on the results of experimental tests conducted on cattle. Improvements were made to the algorithm for constructing the interval neutrosophic fuzzy Sugeno model for the purpose of diagnosing cattle diseases. This improved algorithm is designed to increase the reliability of the process of diagnosing diseases in cattle. Based on the developed algorithm, a model for diagnosing diseases in cattle was created. The results were compared with the Sugeno fuzzy-logical model, the group argument accounting method, and the mathematical model of E. Shortliffe. During the comparative analysis, our model demonstrated better results compared to other models.

In this study, a method for diagnosing cattle diseases based on interval neutrosophic logic has been developed and presented. The main achievement of the work is the creation of the interval neutrosophic Sugeno model, which allows for the uncertainty and inconsistency of data, ensuring diagnostic accuracy at the level of 92%. The comparative analysis confirmed the superiority of the proposed model over existing methods, including classical Sugeno models and the Shortliffe mathematical model, especially in problems with a high degree of uncertainty. The use of the proposed methodology helps to increase the accuracy and reliability of diagnostic solutions, which makes it promising for implementation in veterinary practice. The model also demonstrates its versatility, due to which it can be adapted to diagnostic problems.

It is necessary to adapt the developed approach for diagnosing diseases in other animal species (e.g. horses, sheep and birds), which will allow the model to be used in a wider range of veterinary problems. Development of animal health monitoring systems based on the proposed model and Internet of Things (IoT) sensors, such as temperature, pulse and activity meters, will ensure continuous monitoring of the animals' condition and prompt diagnostics. Evaluation of the economic benefits of using the developed approach in real farm conditions, including reduced diagnostic costs and increased productivity. Further work in these areas will expand the capabilities of the proposed model and increase its applicability in practical conditions, which will contribute to improving animal health and the economic stability of farms.

Appendix A

Example 1. Let's assume that $X = [x_1, x_2]$ these are 2 signs of cattle diseases. Meanings x_1 and x_2 are situated in $[0,1]$. They are sourced from experts in the veterinary field and can be graded as good, vague, or bad. A represents interval neutrosophic set X defined by the formula

$$
\begin{aligned}
&A = X_1 = \\
&= \left(\left[0.81, \quad 0.96\right], \left[0.021, \quad 0.04\right], \left[0.02, \quad 0.04\right]\right)/x_{1.1} + \\
&\left(\left[0.83, \quad 0.94\right], \left[0.031, \quad 0.06\right], \left[0.03, \quad 0.06\right]\right)/x_{1.2} + \\
&\left(\left[0.83 \quad 0.98\right], \left[0.01, \quad 0.02\right], \left[0.01, \quad 0.02\right]\right)/x_{1.3} + \\
&\left(\left[0.88, \quad 0.93\right], \left[0.04, \quad 0.07\right], \left[0.05, \quad 0.07\right]\right)/x_{1.4} + \\
&\left(\left[0.81, \quad 0.98\right], \left[0.012, \quad 0.01\right], \left[0.01, \quad 0.02\right]\right)/x_{1.5} + \\
&\left(\left[0.80, \quad 0.99\right], \left[0.05, \quad 0.01\right], \left[0.05, \quad 0.01\right]\right)/x_{1.6}.
\end{aligned}
$$

B is the interval neutrosophic set X , defined by the formula

$$
\begin{aligned}
&B = X_2 = \\
&= \left(\left[0.70, \quad 0.90\right], \left[0.018, \quad 0.02\right], \left[0.02, \quad 0.03\right]\right)/x_{2.1} + \\
&\left(\left[0.81, \quad 0.90\right], \left[0.026, \quad 0.04\right], \left[0.01, \quad 0.04\right]\right)/x_{2.2} + \\
&\left(\left[0.81 \quad 0.94\right], \left[0.01, \quad 0.02\right], \left[0.01, \quad 0.02\right]\right)/x_{2.3} + \\
&\left(\left[0.84, \quad 0.90\right], \left[0.02, \quad 0.09\right], \left[0.07, \quad 0.09\right]\right)/x_{2.4} + \\
&\left(\left[0.80, \quad 0.95\right], \left[0.010, \quad 0.01\right], \left[0.01, \quad 0.02\right]\right)/x_{2.5} + \\
&\left(\left[0.75, \quad 0.94\right], \left[0.03, \quad 0.01\right], \left[0.04, \quad 0.01\right]\right)/x_{2.6}.
\end{aligned}
$$

Example 2. Let A and B be the interval neutrosophic sets defined in Example 1. Then the intersection

$$
\begin{aligned}
&A \cap B = X_1 \cap X_2 = \\
&= \left(\left[0.70, \quad 0.90\right], \left[0.021, \quad 0.04\right], \left[0.02, \quad 0.04\right]\right)/x_{3.1} + \\
&\left(\left[0.81, \quad 0.90\right], \left[0.031, \quad 0.06\right], \left[0.03, \quad 0.06\right]\right)/x_{3.2} + \\
&\left(\left[0.81 \quad 0.94\right], \left[0.01, \quad 0.02\right], \left[0.01, \quad 0.02\right]\right)/x_{3.3} + \\
&\left(\left[0.84, \quad 0.90\right], \left[0.04, \quad 0.09\right], \left[0.07, \quad 0.09\right]\right)/x_{3.4} + \\
&\left(\left[0.80, \quad 0.95\right], \left[0.012, \quad 0.01\right], \left[0.01, \quad 0.02\right]\right)/x_{3.5} + \\
&\left(\left[0.75, \quad 0.94\right], \left[0.05, \quad 0.01\right], \left[0.05, \quad 0.01\right]\right)/x_{3.6}.
\end{aligned}
$$

Example 3 Let A and B be interval neutrosophic sets defined in example 1.
Then

$$A \cup B = X_1 \cup X_2 =$$
$$= \left(\left[0.81, \quad 0.96\right], \left[0.018, \quad 0.02\right], \left[0.02, \quad 0.03\right] \right) / x_{4.1} +$$
$$\left(\left[0.83, \quad 0.94\right], \left[0.026, \quad 0.04\right], \left[0.01, \quad 0.04\right] \right) / x_{4.2} +$$
$$\left(\left[0.83 \quad 0.98\right], \left[0.01, \quad 0.02\right], \left[0.01, \quad 0.02\right] \right) / x_{4.3} +$$
$$\left(\left[0.88, \quad 0.93\right], \left[0.02, \quad 0.07\right], \left[0.05, \quad 0.07\right] \right) / x_{4.4} +$$
$$\left(\left[0.81, \quad 0.98\right], \left[0.010, \quad 0.01\right], \left[0.01, \quad 0.02\right] \right) / x_{4.5} +$$
$$\left(\left[0.80, \quad 0.99\right], \left[0.03, \quad 0.01\right], \left[0.04, \quad 0.01\right] \right) / x_{4.6}.$$

Literature

1. L. A. Zadeh , Fuzzy sets, Inf. Control 8 (1965), 338–353.
2. L. A. Zadeh . Fuzzy sets as a basis for a theory of possibility. Fuzzy Sets and Systems Volume 100, Supplement 1, 1999, Pages 9-34
3. L. A. Zadeh . A fuzzy-algorithmic approach to the definition of complex or imprecise concepts. International Journal of Man-Machine Studies Volume 8, Issue 3, May 1976, Pages 249-291
4. I. Turksen , Interval valued fuzzy sets based on normal forms, Fuzzy Sets and Systems 20 (1986), 191–210.
5. Hongwu Qin, Yanan Wang, Xiuqin Ma, Jin Wang, Chen Jiang. A Euclidean Distance-based parameter reduction algorithm for interval-valued fuzzy soft sets. Expert Systems with ApplicationsVolume 234, 30 December 2023, 121106
6. Jianhua Dai, Zhiyang Wang, Weiyi Huang. Interval-valued fuzzy discernibility pair approach for attribute reduction in incomplete interval-valued information systems. Information Sciences Volume 642, September 2023, 119215
7. N. Karnik and J. Mendel, Introduction to type-2 fuzzy logic systems, Proc. 1998 IEEE Fuzz Conf., 1998, pp. 915–920.
8. Marcin Woźniak, Józef Szczotka, Andrzej Sikora, Adam Zielonka. Fuzzy logic type-2 intelligent moisture control system. Expert Systems with Applications Volume 238, Part A, 15 March 2024, 121581
9. İhsan Erozan, Emre Özel, Damlanur Erozan. A two-stage system proposal based on a type-2 fuzzy logic system for ergonomic control of classrooms and offices. Engineering Applications of Artificial Intelligence Volume 120, April 2023, 105854
10. Qilian Liang and Jerry M. Mendel, Interval type-2 fuzzy logic systems: Theory and design, IEEE Transactions On Fuzzy Systems 8 (2000), no. 5, 535–55
11. Ayfer Ergin a, Baris Sandal. Mobbing among seafarers: Scale development and application of an interval type-2 fuzzy logic system. Ocean Engineering Volume 286, Part 1, 15 October 2023, 115595
12. Primova, H., Safarova, L. The predictive model of disease diagnosis osteodystrophy cows using fuzzy mechanisms logic; AIP Conference Proceedings, 2021, 2365, 050005
13. J. Mendel and R. John, Type-2 fuzzy sets made simple, IEEE Transactions on Fuzzy Systems 10 (2002), 117–127
14. Muhamediyeva, D. Safarova, L Tukhtamurodov, N. Neutrosophic Sets and Their Decision-Making Methods on the Example of Diagnosing Cattle Disease; International Conference on Information Science and Communications Technologies: Applications, Trends and Opportunities, ICISCT 2021,
15. K. Atanassov , Intuitionistic fuzzy sets, Fuzzy Sets and Systems 20 (1986), 87–96.
16. Muhamediyeva, D.T. Safarova, L.U. Tukhtamurodov, N. Early diagnostics of animal diseases on the basis of modern information technologies AIP Conference Proceedings, 2023, 2817, 02003

17. Muhamediyeva, DT Safarova, LU Tukhtamurodov, N. Building a fuzzy sugeno model for diagnosing cattle diseases on the basis of developing a knowledge base; AIP Conference Proceedings, 2023, 2817, 020037
18. Two variants of intuitionistic fuzzy propositional calculus, Preprint IM-MFAIS-5-88, 1988.
19. Turimov Mustapoevich, D., Muhamediyeva Tulkunovna, D., Safarova Ulmasovna, L., Primova, H., Kim, W. Improved Cattle Disease Diagnosis Based on Fuzzy Logic Algorithms. Sensors, 2023, 23(4), 2107
20. Primova, H.A., Mukhamedieva, D.T., Safarova, L..Application of Algorithm of Fuzzy Rule Conclusions in Determination of Animal's Diseases Journal of Physics: Conference Series, 2022, 2224(1), 012007
21. Safarova, L.. Formation of informative signs for predicting the disease of highly productive cows with non-communicable diseases Journal of Physics: Conference Series, 2021, 1901(1), 012049
22. K. Atanassov and G. Gargov , Intuitionistic fuzzy logic, Compt. Rend. Acad. Bulg. Sci. 43 (1990), 9–12.
23. Sikdar Md. S Askari, Md. Anwar Hussain. IFDTC4.5: Intuitionistic fuzzy logic based decision tree for E-transactional fraud detection. Journal of Information Security and Applications Volume 52, June 2020, 102469
24. K. Atanassov and George Gargov , Elements of intuitionistic fuzzy logic. part i , Fuzzy Sets and Systems 95 (1998), 39–52.
25. J. Jansi Rani, A. Manivannan. An application of generalized symmetric type-2 intuitionistic fuzzy variables to a transportation problem with the effect of a new ranking function. Expert Systems with Applications Volume 237, Part A, 1 March 2024, 121384
26. Kaan Deveci, Önder Güler. Ranking intuitionistic fuzzy sets with hypervolume-based approach: An application for multi-criteria assessment of energy alternatives. Applied Soft Computing Volume 150, January 2024, 111038
27. S. de Amo , W. Carnielli , and J. Marcos, A logical framework for integrating inconsistent information in multiple databases, Proc. PoIKS'02, LNCS 2284, 2002, pp. 67–84.
28. N.C.A.D. Costa, On the theory of inconsistent formal systems, Notre Dame Journal of Formal Logic 15 (1977), 621–630
29. N. D. Belnap , A useful four-valued logic, Modern Uses of Many-valued Logic (G. Eppstein and J. M. Dunn, eds.), Reidel , Dordrecht, 1977, pp. 8–37.
30. A unifying field in logics: Neutrosophic logic. neutrosophy, neutrosophic set, neutrosophic probability and statistics, Xiquan, Phoenix, 2003, third edition.
31. F. Smarandache, A unifying field of logics. Neutrosophy: neutrosophic probability, set and logic, Rehoboth, American Research Press, 1998.
32. Mehmet S Theory and Applications of Mathematics & Computer Science 6 (1) (2016) 1–12 // An Application of Fuzzy Sets to Veterinary Medicine, Nev¸ sehir HBV University, Department of Mathematics, 2000 Evler. 50300 Nev¸sehir, Turkey.
33. Jae-Neung Lee, Myung-Won Lee, Yeong-Hyeon Byeon, Won-Sik Lee, and Keun-Chang Kwak Classification of Horse Gaits Using FCM-Based Neuro-Fuzzy Classifier from the Transformed Data Information of Inertial Sensor Department of Control and Instrumentation Engineering, Chosun University, 375 10 May 2016 Sensors 2016, 16, 664; doi:10.3390/s16050664.
34. Susana Brás, Lénio Ribeiro, David A. Ferreira, Luis Antunes, Catarina S Nunes Controlling the Hypnotic Drug (propofol) to maintain a stable depth of Anesthesia, in Dogs. 978-1-4799-2921-4/14/$31.00 ©2014 IEEE.
35. Ferreira L., Yanagi-Jr T., Nããs I.A., and Lopes M. A., "Development of a Decision-Making System Using Fuzzy Logic to Predict Estrus in Dairy Cows", Agricultural Engineering International: the CIGR Ejournal. Manuscript IT 06 004. Vol. IX. September, 2007. 1-16.
36. Firk R., Stamer E., Junge W., and Krieter J., 2003. Improving oestrus detection by combination of activity measurements with information about previous oestrus cases. Livestock Production Science82: 97-103.

37. Mauro Zaninelli, Francesco Maria Tangorra, Annamaria Costa, Luciana Rossi Vittorio Dell'Orto, Giovanni Savoini Sensors. Improved Fuzzy Logic System to Evaluate Milk Electrical Conductivity Signals from On-Line Sensors to Monitor Dairy Goat Mastitis/ doi:10.3390/s16071079 www.mdpi.com/journal/sensors 2016 by the authors; licensee MDPI, Basel, Switzerland. Published: 13 July 2016/ p 1-18.
38. Ameen A. A. Mikail N., Live body weight prediction in hair goats by application of fuzzy logic / Applied ecology and nvironmental research 16(6):7563-7574. http://www.aloki.hu ISSN 1589 1623 (Print) ISSN 1785 0037 (Online) DOI: http://dx.doi.org/10.15666/aeer/1606_75637574, 2018, ALÖKI Kft., Budapest, Hungary // p 7563-7574.
39. The Fuzzy Model for Diagnosis of Animal Disease Xiao Jianhua, Shi Luyi, Zhang Yu, Gao Li, Fan Honggang, Ma Haikun, and Wang Hongbin D. Li and C. Zhao (Eds.): CCTA 2009, IFIP AICT 317, pp. 364–368, 2010. © IFIP International Federation for Information Processing 2010.
40. Qayyum, A., Mushtaq, N., Shaheen, T., Ali, W., & Smarandache, F. (2024). Some Similarity Measures on Generalized Interval-Valued Intuitionistic Fuzzy Soft Expert Sets and Their Applications in Medical Diagnosis. Neutrososophic Systems With Applications, 23, 47-67. https://doi.org/10.61356/j.nswa.2024.23398
41. Narmadhagnanam, R. and Samuel, A. E. (2024). Applications of secant projection in medical diagnostics. Neutrosophic Systems With Applications, 18, 40–45. https://doi.org/10.61356/j.nswa.2024.18254.
42. Dhanalakshmi, P. . (2024). Coarse Fermata neutrosophic sets and their application in medical diagnostics. Neutrosophic Systems With Applications, 18, 31–39. https://doi.org/10.61356/j.nswa.2024.18261
43. F. Smarandache, Linguistic paradoxes and tautologies, Libertas Mathematica, University of Texas at Arlington, IX (1999): 143-154.
44. F. Smarandache, Neutrosophic set – a generalization of intuitionistic fuzzy sets, International Journal of Pure and Applied Mathematics 24(3) (2005): 287-297.
45. F. Smarandache, Neutrosophic set – a generalization of intuitionistic fuzzy set, Journal of Defence Resources Management 1(1) (2010): 107-116
46. H. Wang, F. Smarandache, Y.Q. Zhang, and R. Sunderraman, Single valued neutrosophic sets, Multispace and Multistructure 4 (2010): 410-413
47. H. Wang, F. Smarandache, Y.Q. Zhang, and R. Sunderraman, Interval Neutrosophic Sets and Logic, Hexis, Arizona, 2005.
48. Interval Neutrosophic Sets and Logic: Theory and Applications in Computing Haibin Wang, Florentin Smarandache, Yan-Qing Zhang, Rajshekha Sunderraman, Department of Computer Science Georgia State University Atlanta, GA 30302, USA Department of Mathematics and Science University of New Mexico Gallup, NM 87301, USA Hexis Arizona 2005
49. Qilian Liang and Jerry M. Mendel, Interval type-2 fuzzy logic systems: Theory and design, IEEE Transactions On Fuzzy Systems 8 (2000), no. 5, 535–550.
50. Takagi T., Sugeno M. Fuzzy Identification of Systems and Its Applications to Modeling and Control // IEEE Trans. on Systems, Man, and Cybernetics. Vol. 15, № 1. - 1985. - P. 116 - 132.
51. Yager R., Filev D. Essentials of Fuzzy Modeling and Control. USA: John Wiley & Sons. - 1984. - 387p.
52. SB Eshburiev.Etiopathogenesis and prevention of secondary osteodystrophy of cows. 2011 Ph. D. Thesis 122
53. SB Eshburiev, BM Eshburiev. An effective method for preventing disorders of vitamin and mineral metabolism in cows. The Way of Science Volume 34. 2014/3
54. Sobir Bakhtiyorovich Eshburiev, Kurban Narbaev, Nikolai Mikhailovich Kostomakhin. Group prevention of vitamin and mineral metabolism disorders in highly productive cows. Magazine Chief Livestock Specialist. 2017 Number 11 Pages 3-8
55. Muhamediyeva, D.K. Nurumova, A.Y., Muminov, S.Y., Fuzzy evaluation of cotton varieties in the natural climatic. IOP Conference Series: Earth and Environmental Science, 2022, 1076(1), 012043.

56. V.V. Serebrovsky, V.V. Fedyanin, S.N. Korenevskaya, A.V. Serebrovsky Using fuzzy decision logic mechanisms to assess the condition of humans and animals (using the example of prediction and diagnosis of pyelonephritis) Kursk State Agricultural Academy: Publishing house Kursk, state. agricultural ak., 2015. - 123 p.

Received: Nov. 11, 2024. Accepted: April 6, 2025