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Development of a Technique for Discrete-Logical Decision-Making in Medical Information Systems

Islam A. Alexandrov [1*], Vladimir Zh. Kuklin [1], Leonid M. Chervyakov [1], Sergei A. Sheptunov [1]

[1] *Institute of Design and Technology Informatics, Russian Academy of Sciences, Russian Federation.*

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Abstract

One of the urgent directions in solving medical diagnostic tasks is to develop new and improved decision support systems capable of efficiently processing polymodal data. Humans cannot always process large arrays of medical information and determine an accurate diagnosis in complex situations. Thus, improving the functioning of the industry requires implementing a variety of systems capable of supporting decision-making of one kind or another. The presented technique aims to steadily increase the level and speed, and demonstrate the feasibility of integrating non-classical logic into the structure of the decision-making system in medical research by using non-classical logic complexes. The main advantage of the proposed approach is that it achieves the necessary level of information criteria; in particular, it provides the required information quality, high reliability of the decision, its value, preserves the amount of information, and searches and decision-making take relatively small-time intervals. This paper presents an overview of various non-classical logics and, based on the analytical findings, delineates the optimal choice of logic for each stage in the development of a decision support system. The processing and feedforward structures for DSS are presented based on selected types of non-classical logic. The algorithms presented for solving decision-making problems are based on discrete-logic approximations of a priori and actual data, which are optimal or suboptimal, and they use information and value criteria. The abstraction of any problem situation relies on using means operating with frequency and comparative logic to provide logical approximations of the sought characteristics. The accuracy of the diagnostic decisions reached 97% when using the developments presented in this study.

Keywords: Approximation; Decision-Making; Diagnosis; Logic; Reliability.

1. Introduction

Sometimes, when making a diagnostic conclusion or management decision, specialists must work with polymodal information of various formats, characterized by definite errors and contradictions, which significantly complicate the formation of formal models and the development of a correct decision. Accurate and early diagnosis would also prevent the progression of chronic diseases. A disease may present with symptoms that are similar to those of other diseases, which could lead to confusion, even among the most experienced physicians. Furthermore, a patient may exhibit a combination of symptoms that can be attributed to multiple diseases, which may not be easily quantifiable. When observing these symptoms, physicians with varying professional levels and clinical experience may differ in their diagnosis, potentially leading to misdiagnosis. Additionally, patients may be uncertain about their symptoms, which

* Corresponding author: islam.alexandrov@rambler.ru

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could impede the accuracy of diagnosis. Therefore, there is a need for a toolkit capable of processing contradictory and even low-value information with greater accuracy and subsequent integration of heterogeneous data [1, 2].

Decision-support complexes are becoming more in demand owing to the constant shortage of time, insufficiently developed resource bases, and lack of qualified personnel. In addition, there is often a lack of accurate and unambiguous information about a particular study object, which complicates medical diagnosis and subsequent therapy. Constantly increasing the volume of data and information materials for certain diseases in medicine cannot be promptly studied by a single specialist. In the future, this situation will only worsen [3].

Automating the treatment process is perhaps the most promising direction for creating complexes capable of supporting decision-making. In addition, it is necessary to gradually improve each subsystem responsible for the logical conclusions that explain and confirm the obtained results and the use of complexes of objective logic based on information semasiology. Moreover, the basis for creating the considered models should be indirect appeal [4, 5].

Today, researchers worldwide conduct a great deal of research to solve the primary problem, but they often neglect the incompleteness of information about medical processes. The virtual absence of efficient tools to specify the structure of logical conclusions and to ensure systematic work with incomplete information causes additional problems.

In the domain of knowledge representation and reasoning, a pivotal field of inquiry in Artificial Intelligence, non-classical logic assumes a pivotal dual role: firstly, non-classical logical languages facilitate the precise and transparent encapsulation of domain-specific knowledge. Secondly, as logical languages are endowed with distinctive rules pertaining to logical inference, they offer a systematic methodology for deriving novel insights from prior information [6].

Decision quality often depends on the decision-maker’s knowledge. The main task of a decision support system is to offer several options for a decision (in the specific case of a diagnosis for a patient) and clearly explain the information or parameters for decision-making. When such a structure works, it will be much easier for the specialist to make a quality decision (most appropriate for the situation). It is imperative to address the issue of exponential growth in the time and memory requirements of logic processes with the increasing dimensionality of tasks and proliferation of enumeration alternatives. Furthermore, it is essential to recognize the potential for utilizing a DSS to provide a value assessment of the decision made. This study aims to improve the quality of medical decisions made by specialized professionals based on diagnosis results, conclusions of non-classical logic, and semantics. The result is forming a task related to creating a system of rational use of diverse a priori and factual data of medical characteristics.

2. Literature Review

The decision-making procedure is definite work on forming and analyzing alternatives. Using tools that support decision-making is necessary for selecting and evaluating the best options from massive amounts of data [7]. In this process, it is essential to thoroughly examine the purposive samples that are the basis for decision making, identify the alternatives that deserve subsequent attention, and finally select a particular decision [8]. Medical practice shows that implementing each measurement, observation, and accumulation of necessary data requires improvement. However, specialized professionals fail to process continuously increasing volumes of data [4].

Medical diagnosis, a combination of transcendental and posteriori stages, has particular cyclicality [5, 9]. For this reason, computerized medical data processing tools can be divided into

- Information and search complexes, which order, systematize, and concentrate the target data according to the clear conclusions of a specialized professional.
- Complexes capable of processing incoming data using ordered chains of operations based on simulations of certain known situations.

Chen et al. [10], Schaaf et al. [11], and Sutton et al. [12] studied on the software potential of specialized machines designed to provide automated evaluation of available medical data, which is essential because, in practice, many objective and subjective factors make manual evaluation of available data difficult. These include, first, a continuously increasing information flow with sufficient limited resources of processing means, various errors and mistakes, and significant time for making adequate and accurate decisions.

Medical professionals employ a range of techniques to diagnose cardiovascular disease, including physical examination, analysis of a patient's medical history, and performance of a variety of medical tests. Notably, a significant proportion of individuals who have experienced a myocardial infarction or cerebrovascular accident have not been identified as being at an elevated risk by medical experts and specialists. Approximately 30% of cases have been misdiagnosed by specialists. This is largely attributed to the inherent challenges associated with the accurate diagnosis of cardiovascular disease, including the lack of overt symptoms in patients or the use of examination methods that are not sufficiently specific. Consequently, the accuracy of diagnostic tests is limited in determining the presence or absence of a disease. Consequently, the interpretation of test results requires the expertise of a highly qualified specialist to accurately identify the underlying disease process [13, 14].

In recent years, there has been considerable interest in the potential of combining medical sensors with artificial intelligence algorithms, with significant progress being made in this field. Meanwhile, the current range of out-of-body detection devices exhibits low levels of automation, specificity, and stability and requires complex sample pre-processing. The fabrication of sensors for near-body monitoring is a complex process because of the large surface area and the intricate network of interconnected lines. The quality of the interface between the sensor and target organ is crucial for the efficiency of signal acquisition. Disease prediction using DSS is a challenging task because most platforms focus on health characteristics alone, neglecting potential disease signals. This limits their ability to serve as early warning systems. Therefore, a software platform should have a deep understanding of the medical needs and challenges to simultaneously achieve specialization and practicality [15, 16].

It is important to emphasize that diagnoses must operate with significant arrays of transcendental data. It must be valid, but because of the constant increase in the volume of incoming information, we will observe a substantial reduction in the reliability of the final decisions [17-19]. For this reason, it makes sense to outline the key issues concerning decision-making procedures. We should not forget that evaluation, management, and design have their peculiarities, so we propose to consider the formulation of the inverse problem in medical diagnostics in detail [20, 21].

Let us now analyze existing concepts to identify similarities in decision-making systems. First, we focus on the Bayesian approach, whose main advantage is the possibility of determining apodictic distributions based on transcendental distributions. This method is applicable for the realization of spheres operating with massive statistical arrays. The results of many studies demonstrate that humans do not rely on existing knowledge but prefer to study more relevant information [22-24].

The calculation of the conditional probability is as follows:

$$p(x|y) = \frac{p(x,y)}{p(y)} \tag{1}$$

here, $p(x|y)$ is the probability of event x or y. Therefore, $p(xy)$ corresponds to $p(x|y)p(x)$. By dividing the two components of this ratio by the current value $p(y)$, we obtain the rules proposed by Bayes: $p(y|x)p(x) = p(y)p(x|y)$,

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)}. \tag{2}$$

Another approach involving the active use of neural networks is a universal approximation algorithm with high data-processing speed. Generally, a neural network is a complete bipartite graph with neurons as nodes and edges that describes the level of mutual connections characterized by slowing pulses. At the same time, a neural network is a sensory complex whose 1st half is sensors, and the 2nd half is responsible for creating specific subsystems [25, 26]. The activation function is defined as follows:

$$f(x) = \sigma(x) = \frac{1}{1+e^{-x}} \tag{3}$$

Other variations in the activity definition are also possible, such as the introduction of special nonlinear differential functions.

The evolutionary algorithm is the most common among the genetic algorithms [1, 27]. It involves selecting the most powerful objects and the subsequent generation of search objects by introducing dependencies covering several arguments, which makes it possible to capture the presence of the largest and smallest values. The reproduction process involves executing the following four steps simultaneously: selection, crossover, mutation, and inversion. A characteristic feature of this approach is that the primary work on model building is transferred to the modified algorithm.

Fuzzy logic is a helpful tool for describing systems with statistically distributed data, and the analytical description is complicated because the problems are weakly formalizable. As a generalization of classical logic and set theory, fuzzy logic operates using membership functions, output operators, and linguistic variables as fuzzy sets. This approach helps model the state parameters of different systems, allowing it to pass from qualitative to quantitative descriptions. For example, triangular and trapezoidal membership functions, transforming linguistic variables, are applied for transitioning from qualitative expert estimations of good, bad, and excellent. As a result of these opportunities, fuzzy logic methods are applied to supplier selection tasks, decision-making tasks in complex situations, and others [28, 29].

One of the main limitations that hinders the functioning of any medical complex supporting the decision-making process is that the decisions will provide highly accurate results only within the selected areas of knowledge from which they originate, after which they are lost completely [30]. Table 1 summarizes the main advantages and disadvantages of the logical inference methodologies.

Table 1. Description of the main features of logical inference methodologies

Methodology	Advantages	Disadvantages
Bayesian analysis	Highly accurate and reliable results due to exact reliability assessment mechanisms.	It is against the people's wishes to get the most fresh and up-to-date information.
Neural networks	A universal approximation algorithm with the main advantage of high flexibility in selecting settings.	Lack of specific mechanisms to assess the reliability of decisions and rules for changing the algorithm.
Genetic algorithms	The ability to successfully solve highly complex problems characterized by many stochastic connections.	Extremely high subjectivity at the task formulation stage, and difficulties in defining criteria for chromosome selection.
Fuzzy logic	Ability to model complex and weakly formalizable systems. The models built based on fuzzy logic methods have high speed.	Despite describing systems using membership functions and fuzzy sets, the universal technique for building fuzzy models is absent. In addition, many mathematical methods are inapplicable to the analysis of constructed fuzzy models.

3. Objects and Methods of Research

3.1. Complex That Performs Data Processing During Medical Diagnostics

To implement the proposed system, we selected a specific device with information semantics, making it possible to perform logistic approximations with several set parameters. Based on a detailed review of research and theoretical analysis, we conclude that for computerized information processing, the most appropriate solution is to realize the idea of using logical units. In this case, a generalized scheme describing information processing is of interest, as shown in Figure 1. To build any information copies reflecting the dynamics of specific situations, it is better to operate with a priori information, estimating the split positions $q(x,y)$ equal to vector y or x considering estimation errors. In most cases, it makes practical sense to apply statistical information built on the approximation model created by most experts to increase adequacy indicators. Thus, considering the direct distribution $q(x,y)$, several partial and sufficient conditional distributions of x and y were constructed.

The predominant part of the classification decisions represents $\hat{x} = B(y,J)$, where J is the aggregate model information and expert opinion and y represents the amount of empirical data comprising their array. A table of distributions describes a series of quantitative relations covering several core and observable characteristics, often referred to as symptoms. The possibility of good treatment outcomes is one reason for the mandatory completion of each patient's medical records. The overall structure of the payment table, realizing the core indicator, is created either by an expert environment or based on studies of previously collected information. The minimum expected loss is the value criterion:

$$\min_{x} \lambda(y,x) = \min_{x}\Big(\lambda_0 + \frac{1}{q_y}\sum_{x=1}^{r}\lambda(xx)\times q(x,y)\Big)_y$$

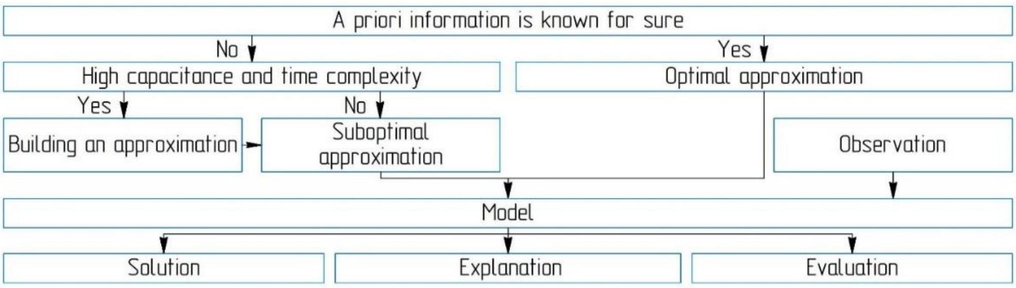


Figure 1. Scheme of using approximation algorithms

The table of payments can take either a positive (the presence of a gain or a profit) or a negative format (losses $\lambda(\hat{y},y,x)$ and unreasonable costs $\lambda_0(\hat{y},x)$). In the end, we witness a negative measure, or we look for the most rational in value terms output, which in any option will guarantee the minimization of losses. The payment matrix then appears to be $\underset{\hat{y}}{min}\{\lambda_0(\hat{y},x + \sum_y \lambda(\hat{y},y,x)q(x,y)$. Computation of the data that allows the estimation of triple or double links between the parameters occurs. Next, the selection of the most significant links from the available array significantly exceeds the value of random fluctuation, and the link threshold established between some categories of parameters [31] proceeds.

3.2. Data Processing Complex

The data processing complex provides comprehensive diagnostic and therapeutic support. The system consists of the following core components, as shown in Figure 2:

- A range of programs that build several helpful approximation characteristics open up the prospect of improvements in the ordered chains of operations responsible for decision-making.

- The complex associated with obtaining reliable information about a particular patient;
- A structure formed from the reference data on which any conclusions are produced by the considered complex.
- A structure that processes incoming data flows may include standardized patient histories that simplify the information spaces of lists of diagnosable characteristics and certain classes in information arrays.

The complex performs a range of functions due to

- Maintaining an information database containing data from each patient. This database stores information about the treatment undertaken and the proposed recommendations for its implementation, according to the algorithms and errors made during the decision-making process;
- Building the best approximations based on all the information available to the specialized professional;
- Developing decisions based on the existing information database and assessing errors in previous decisions, including the burst mode, considering information arrays;
- Issuing recommendations to control the correctness of logical conclusions.

The complex uses an intuitive interface designed for several groups of users:

- Physicians who are the end-users;
- Engineers who form the information base and several specialized experts in the researched area.

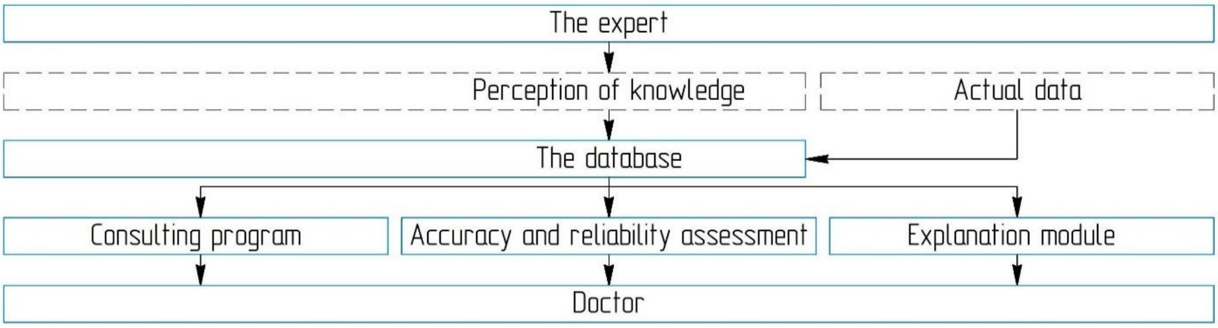


Figure 2. Working scheme of the system

The system uses a tiered structure covering the following:

- The comprehensive consideration and provision of each meaningful spot solution:
    - Complementing each developed spot solution by a sequence reflecting the specifics of the patient's current condition;
    - Forming a separate branch of spot solutions that trace the peculiarities and dynamics of the patient's pathology development;
- Ensuring practical implementation of all decisions corrected by trilogy and tetralogy:
    - Representing the decision that describes the pathology by quaternary grids;
    - Representing the decision that monitors the patient's condition by quadrilateral grids.
- Transformation of incoming medical signals into a frequency spectrum of values continuously analyzed by electronic modules, which then explains the decision:
    - A decision reflecting with sufficient accuracy the current state of the patient using k-th scales;
    - A decision monitoring the patient's condition using k-th scales.

The system's operation relies on diagnosing the current state of patients, ensuring the reliability of all decisions produced by the system.

3.3. Ways to Optimize the Approximation Algorithm

Let us consider several classes of the discussed categories, and by sorting through the existing correlates (an observable feature, trait, or characteristic of the patient), we obtain a new correlate that is more informative than the previous one; therefore, in most cases, it will replace it. A correlate is an observed logical function of attributes with a significant frequency relationship with a target attribute.

We obtained an updated set of correlates at the end of the sorting-through period. Let us denote n as the number of conditions added in the last period, which replaced the previous ones, and m as the number of conditions introduced into the set before retaining their potential in this set. The above corresponds to information indicators relative to the quadratic criterion of the minimum redistributions.

In the next period, we consider several criteria that complete the approximation, owing to the following:

- The volume of helpful data measured in conditional terms;
- Quality of data. This indicator demonstrates the informativeness of objects x, the informativeness of the object concerning the primary object y measured with maximum accuracy characterized by the value of task uncertainty y during the application of memorized information x;
- Values. In this situation, we can discuss the economic or material benefits or harm from applying information or not having information about the current state of $\boldsymbol{x}$. The calculation uses specific tables that describe the effectiveness of the selected decisions or their costs.

Several reference characteristics of object regions and the quality of the algorithmic chains of approximation sometimes become peculiar constraints.

- When the current period of the set of correlation characteristics does not change owing to the proposed correlates, the sequence of correlates selected for the study indicates that the process is complete.

Restrictions specify the maximum number of periods considering a priori values and the increased dimensionality of the intersection of each characteristic.

The sequence of final decision making by a specialized professional is iterative, as shown in Figure 3. In the first stage, the professional receives primary information y about the symptoms or syndromes observed in the patient. Given this information, the sequence of symptoms follows, based on the spheres, which consider an array of diverse information and modeling $M(y)$, reflecting the specific disease. Although other cases are possible, this chain describes a stable relationship: n=0; n=1; n>1. All different types of data received are fed into the overall model by transformation. The information processor converts these data into a frequency rating of the patient's condition and converts it into trilogy values.

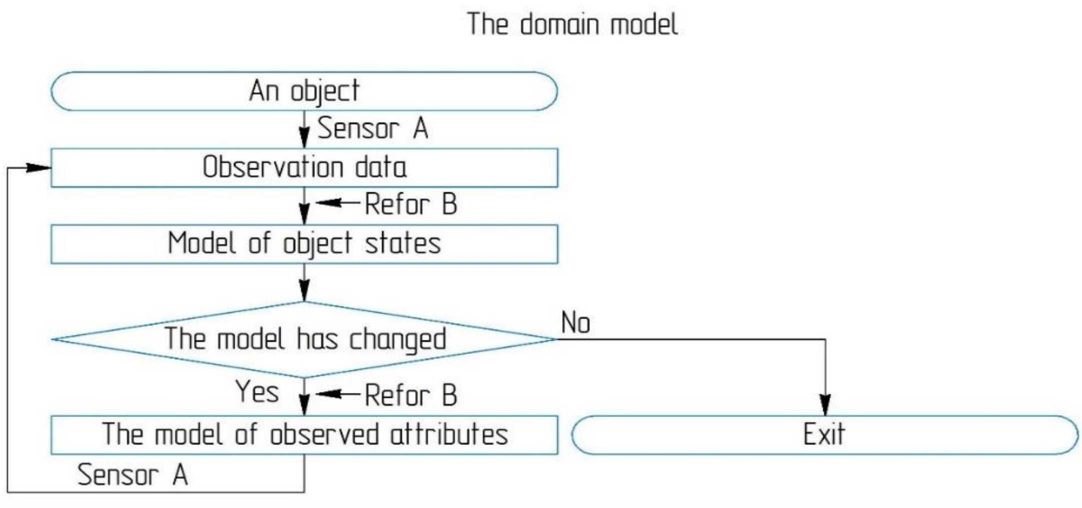


Figure 3. Sequence of decision-making during diagnosis

The first is because the information processor constructs a set that establishes a logical connection between the observed and several base characteristics. The second case emphasizes the presence of an unambiguous logical connection. If there is a correct and complete information processor, this relationship will allow us to conclude that the patient has a disease x. The level of reliability can be assessed either by the results of benchmark testing of the diagnosable algorithms performed previously, by comparing their characteristics, or by their approximation. The third case describes a situation where a diagnosis model is possible, in which the value of p can be transferred into k-approximation logic.

Over time, given this model, the information processor builds a model y that describes most of the observable characteristics present in the studied object. We assumed that the task is approximated as a logical function. Here, any of the functions looks like the sum of each conjunctive element taken from the set. We assume that any attribute can take values equal to one, and the rest will have internal uncertainty. Therefore, according to the principle of decision uncertainty, we calculated the values corresponding to $\{0,1,\theta\ \}$. If we partition the space into several non-intersecting targets until we get a value called "positive implicative function" equal to 1, it means only one thing: the diagnostic period is over. If one or more values are considered equal, we will need to perform additional studies are required to reduce the frequency of observations. For this purpose, we distinguish a set of characteristics $\{y\}$. In most cases, they will transform the current values of dependencies from 1 or 0 on the background of positive or negative responses, confirming or denying the desired objective, which will depend on whether the type of implication (patient attribute that was identified based on the correlates presented) is positive or negative. It is essential to emphasize only the characteristics specific to this situation to identify the purpose. If there is a variant of overlap between each base characteristic, most of the shared attributes will disappear, and only the sphere that emphasizes their distinctiveness will remain.

It is worth considering the available attributes that will not occur in any conjunct of the implicative function represented in the conjunctive normal form (CNF). We propose applying the notation L to the set of each considered component in the CNF. These components can take the values (-1; 0; 1), where -1 acts as one of the indicators, 0 is not specified in this set, and 1 is a positive attribute. The purpose was to minimize the number of additional questions that reduced the non-permanent complexity of diagnosis [32].

The original maximum possible number of sensors corresponds to an established value. We begin the study in the initial column of Figure 4. Next, we look at the sensors that correspond to the components of the table, exceeding 1. When the *i*-th sensor produces some value on the output channel, guided by trilogy, all columns of the table where the *i*-th component is more or less than 0 will be equal. Table 2 shows the relationship between the "ideal" characteristics and sensor readings.

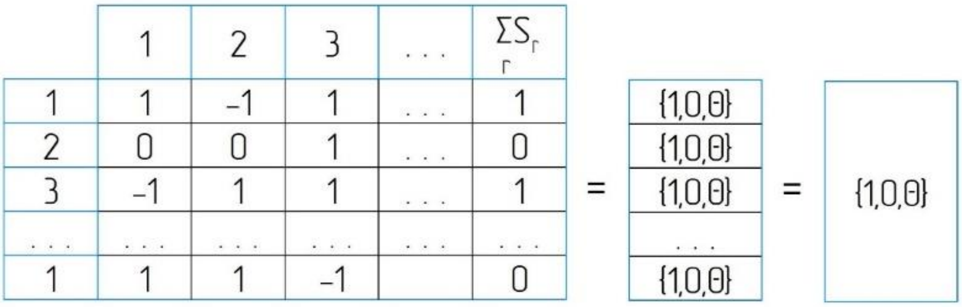


Figure 4. Representation of the implicative function

Table 2. Relationship between the "ideal" characteristics and sensor readings

Sensor	Table	Summary of conjunctions
1	1	–
1	–1	0
0	1	0
0	–1	–

Dashes mean that it will be necessary to continue the study, and when it is not possible, conjunctions will take on other values. If we obtain 0 during the calculation of conjunctions, we can disregard the rest of its attributes because the processes will continue for other conjunctions, relying on known or repeatedly verified information. If we obtain a conjunction corresponding to 1, it will confirm the presence of the task in the case of positive functions or the absence of the task in the case of negative implications, allowing us to complete the basic processes concerning the task implementation. Each 0 value generally prevents the completion of the main processes, because conjunctions should be summarized until one appears. The experiment was conducted when a single conjunction or series took some value, and the remaining ones corresponded to 0. A new disease model will be developed that includes the implicative functions of each target attribute with a value higher than 1. This situation means that the extreme stage of this process did not bring any significant innovations to the sought model, and the process itself did not contribute to reducing uncertainty. Thus, the diagnosis is complete according to the previously generated scenario, which transfers the set into approximation values of *k*-th logic.

3.4. Forms for Submitting Medical Information

One of the necessary properties to optimize the operation of a decision support system (DSS) is the need to isolate complexes that contain information bases and mechanisms that make it possible to draw a valid logical conclusion. The second requirement is the use of a unified form of data provision that simplifies the system saturation procedure with new information and facilitates the processes of this system maintenance. An equally important quality that should characterize the information and each DSS model is the ability to support a function that explains decisions to users [33]. Guided by these requirements, a unified presentation form was formed for each considered model in the system under study. This structure is particularly interesting.

A specific list defines the relationship of each characteristic:

- A complete table: the number of columns;
- A collapsed table: the number of columns;
- A training table: the number of columns with the percentage of references used for the given samples
- Control table: the number of columns.

Each condition transforms into equality when all references are different, and their consolidation does not reduce the number of reference table columns, that is, until the situation occurs when the equalities of all references are different. The initial information is a reference table with form $\{s\}$. Furthermore, it transforms into a distribution table $\{s...\}$. The distribution table contains several moments of only that group of intersections of attributes, which is available in the reference table; the rest are equal to zero and will not enter the distribution table. Most mathematical and logical operations with distribution tables use bitwise logical operations in a standard environment by addition, multiplication, implication, equivalence, and others.

As most modern operating systems are 32-bit, the maximum numbers that allow their processing by bit arithmetic have 32 characters. Figure 5 shows the appearance of an array including 4-byte numbers.

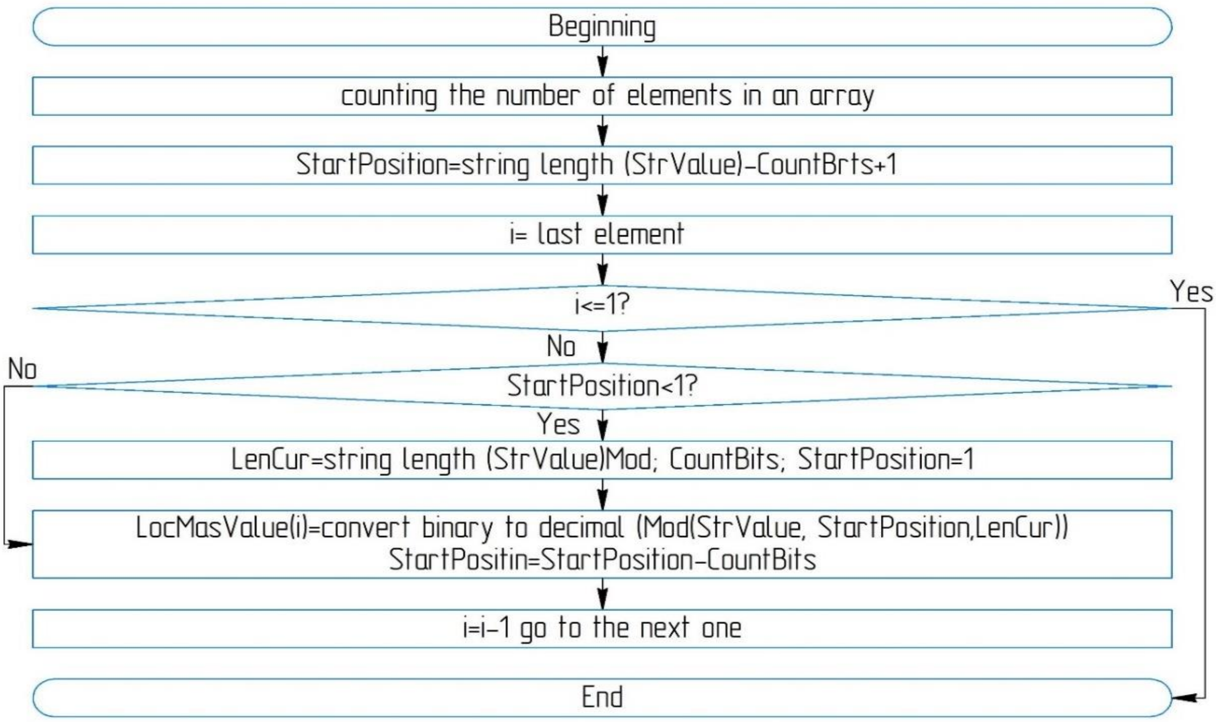


Figure 5. Algorithm, which performs the preparation of the initial information for the use of bitwise operation

The results of comparative tests of different variants of execution of each algorithm, including the implementation of functions characterized by the stock reference representation, demonstrated the maximum performance of the algorithms. It is noteworthy that their operating principle relies on bit arithmetic. Therefore, it is necessary to investigate the main stages of decision-making during diagnosis in the current phase of work.

***Investigation of Base Characteristics*:** For the conjunctions given by the variants given earlier, it is necessary to determine the indicators of achievability, implicativity, and moments and points of intersection with the desired goals. Table columns were investigated using the corresponding calculation in a specific sequence.

Figure 6 shows the structure of the analysis of the characteristics and their intersection points. Implicativity indicators are defined by a method that meets the condition that "any y=1 corresponds to x=1." The achievability indicators satisfy the conditions $q>q_0$ and $q<1–q_0$. Simultaneous calculations improve the efficiency of the algorithms. Figure 7 shows the sequence of splitting attributes into several classes. This stage involves generating all admissible elementary characteristics considering the possibility of their negation. Subsequently, splitting into several classes, consisting of positive and negative implicates and correlates, occurs, ignoring most unattainable characteristics. Figure 8 shows the point exploration algorithm. Here, several correlates obtained earlier are labeled "old." Then, filling this group, its new components will be labeled "new." Grouping correlates into pairs will make it possible to observe all correlates; generating "new" ones uses the "or" bit operator.

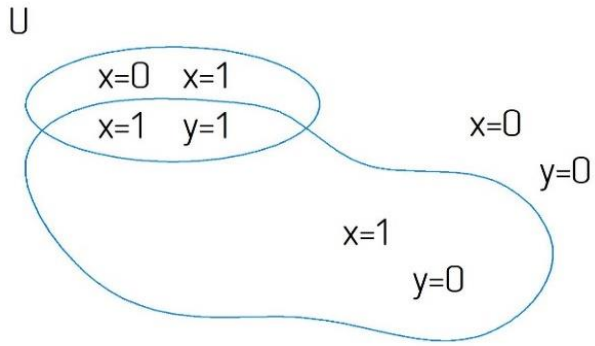


Figure 6. Venn diagram for the considered sets

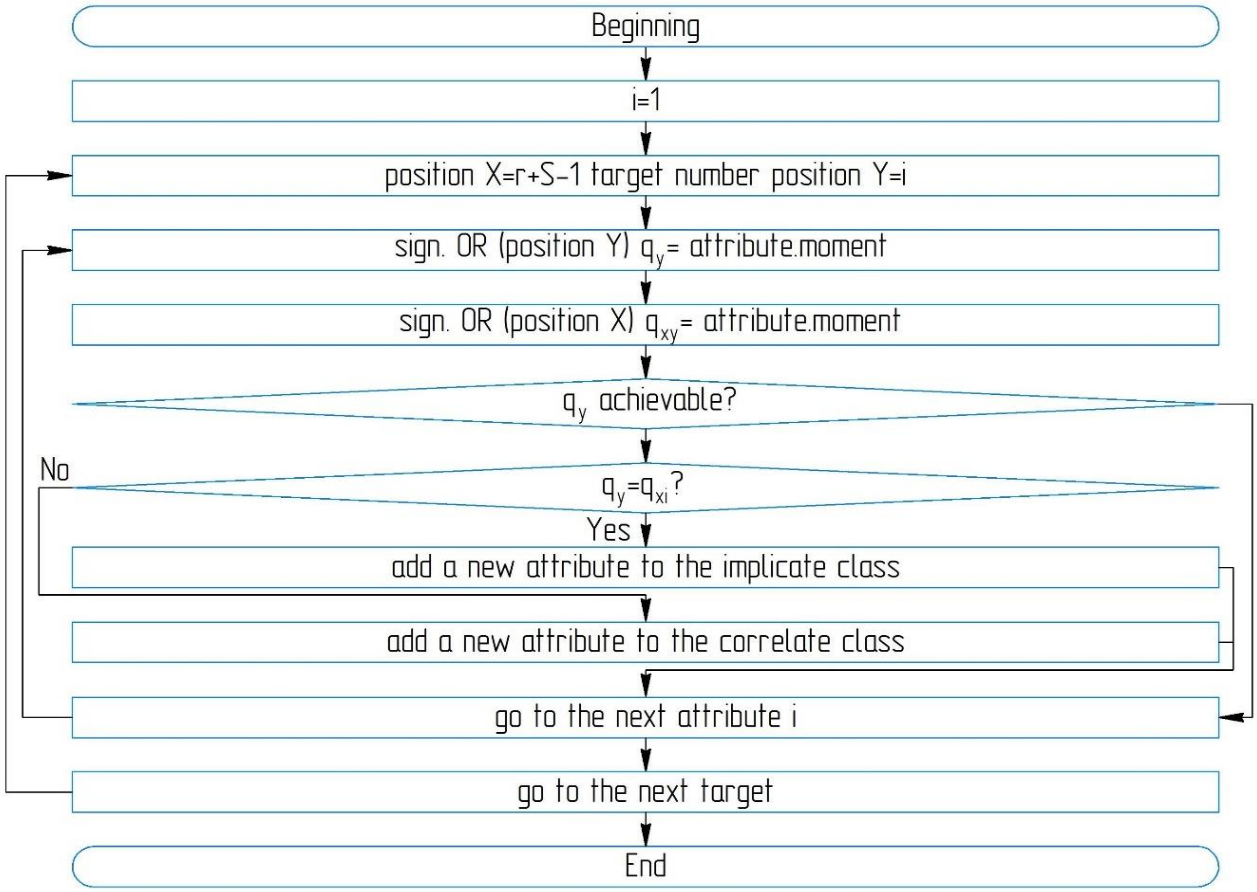


Figure 7. Splitting attributes into several classes

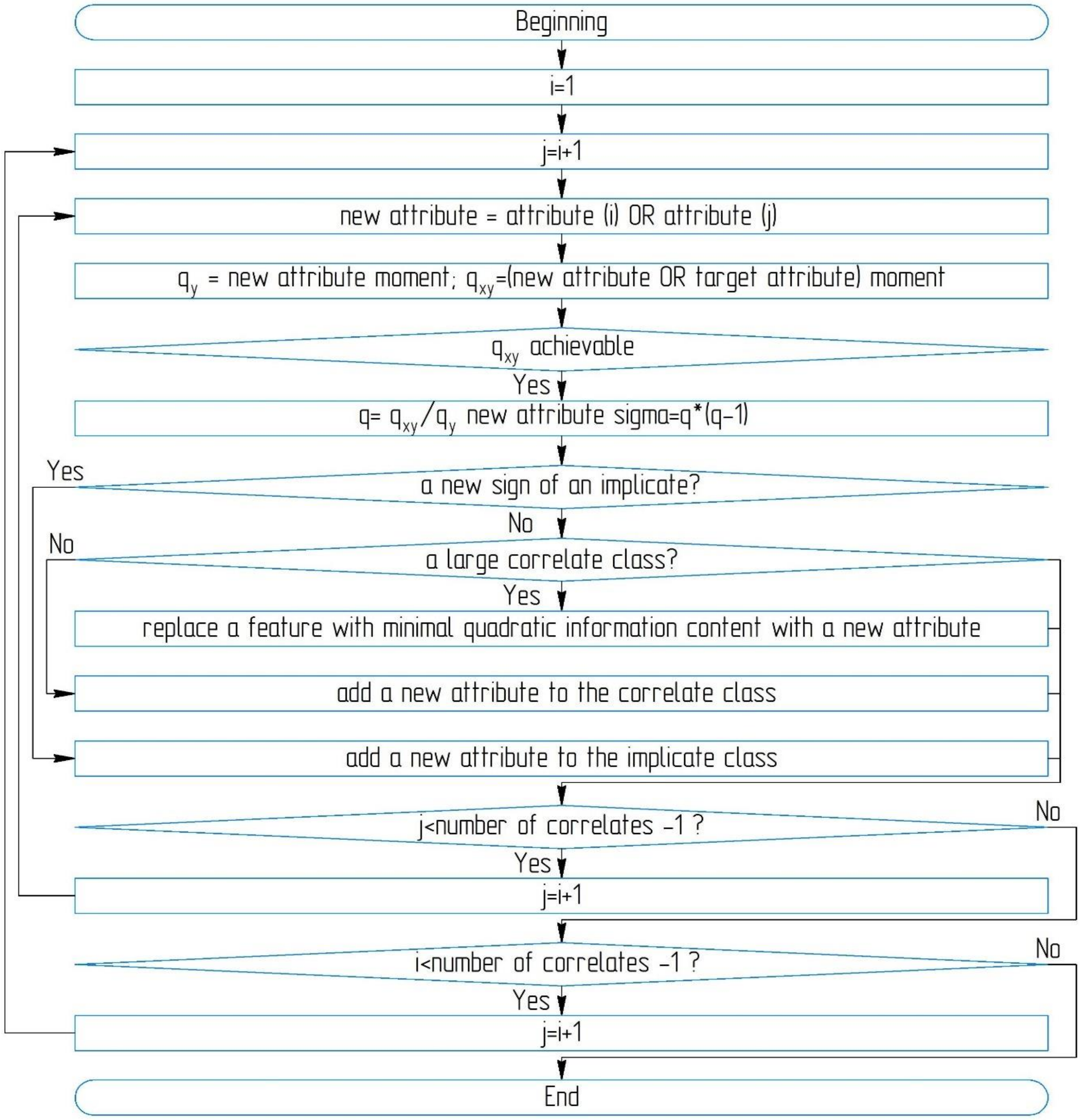


Figure 8. Exploration algorithm of points where the intersection of base characteristics occurs

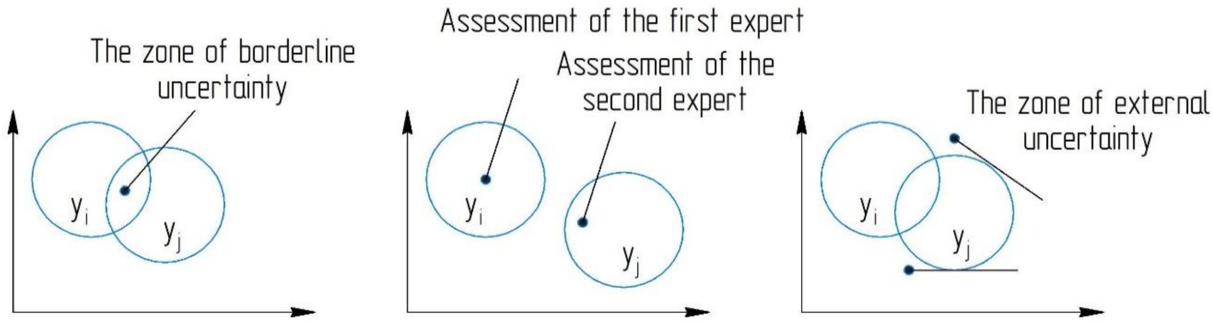
To verify existence, this stage makes it possible to disregard most logically incorrect conjunctions. The examination takes place thanks to the Noma value table without referring to the distribution table and disregarding some format conjunctions {attributes 1 = value 1; attributes 1 = value 2, and so on}, here, values $1 \neq 2$. These are initially considered unattainable, and detecting them without consulting the distribution table is necessary to increase the total efficiency of the algorithms.

3.5. Creation of a Specific Interface Covering Trilogy, Tetralogy, Frequency, and Multivalued Logic

Many experts describe states of objects using the vector "*y*." It is a set of values with attributes in *m* in the importance scale. In this case, the information is not fed to the input channel of *i*-th sensor. Therefore, these characteristics have similar values for evaluating any current characteristics. Each scale meets most evaluation criteria and is applied in many types and formats [34].

Sensors with a nominative scale determine the splitting spaces into several non-overlapping classes, reflecting equivalence. Components that are indistinguishable with respect to a given property populate this group. Sensors with a rank scale specify the splitting of universes and the proper ordering of components by topic. Sensors with logical scales are among the simplest and determine the existence or absence of some attributes. Internal uncertainty is the best confirmation of the qualities of base processes acting under the guise of any sensor indicator and indicates the impossibility of obtaining the desired information. However, they can be the consequence of contradictory overdeterminations of incoming data, for example, in a multi-expert evaluation, as illustrated in Figure 9.

According to the chosen format of the scales, it is possible to use various heuristic techniques to move from internal contradictions to a correct definition of the scale. When a rank scale has a selected ratio, it is the basis for using fuzzy approximations of frequency logic. Sometimes replacing scale values with ones that correspond to the original characteristics is possible while respecting the laws established by trilogy during operations with information discretes [35-37].



1	2	...	i	...	j	...	s_i	Σ_{y_i}
0	0	0	1	0	1	0	0	2<1

1	2	...	i	...	j	...	s_i	Σ_{y_i}
0	0	0	0	0	0	0	0	0<1

Figure 9. Appearance of multi-expert evaluation

Relying on expert conclusions, the considered logical calculations will continue to build a range of implicative functions. In the observation of the patient, the doctor evaluates the attributes in the scale values precisely considering their significance and makes conclusions about the actual sensor states later.

It is worth considering several possible and common errors:

- Kynol, which distorts the majority of studies derived from distorted knowledge, is a variant of fatal errors bordering on the absurd.
- Kinol describes the majority of correctable errors in the information process.

The laws for processing low-value information express the rule of reducing the minimum permissible distortion of data to obtain the necessary decision [38-40]. Following these laws, the form of logical addition will look like $a + b = a$ and the form of logical multiplication – $a \cdot b = a$. Instead, in the course of reduction, it is customary to use a range of transformations of minimal absurdities in the form of internal uncertainty in cases where the investigation of the appeared contradictions suggests such a form. Therefore, it is possible to calculate $L(y)$ according to the rules established in trilogy and tetralogy, and the results take the form of specific values $L(y) \in \{0,1,\theta,-\theta\}$.

3.6. Creating an Explanation Module for Systems Processing Medical Information

The execution of each function explaining the decision on the processing of information arrays will be necessary for the participants to maintain legal responsibility for the decision made, and the developers of the complex should control the correctness of operating all modules, providing logical inference. The creation of explanation modules for each decision depends on the program of the approximation algorithm execution and the composition of the information base. Creation of the explanation will require accessibility to the modeling of object domains, as in the case when information processing occurs, forming the corresponding decisions.

The possibilities of the information process help make a decision $\hat{x} = AB(y, J)$ and offer detailed justifications by the successive implementation of the summary of the observation results. The graphs in Table 3 describe the possible matches $\{x,y\}$ and the allowed variants of the explanations for each decision. Figure 10 shows the interrelation of all components and indicates the correspondence of the information situations.

Table 3. Combinations {*x*,*y*} and possible decision explanations

No.	$\hat{x}$	y	Explanation
			Variant of positive implication
1	2	3	“presence of the characteristic” “will confirm decisions”
2	1	2	“presence of the characteristic” “will refute decisions”
3	θ	0	“the characteristic will not change the decisions made”
4	2	3	“no characteristics” “the decision confirmation”
5	2	2	“no characteristics” “the decision refutation”
6	θ	1	“no characteristics” “decision is unchanged”
			Variant of negative implication
7	2	2	“presence of the characteristic” “the decision refutation”
8	2	0	“presence of the characteristic” “the decision confirmation”
9	θ	2	“decision is unchanged”
10	2	3	“presence of the characteristic” “the decision refutation”
11	1	2	“no characterization” “the decision confirmation”
12	θ	2	“presence of characterization” “decision is unchanged”

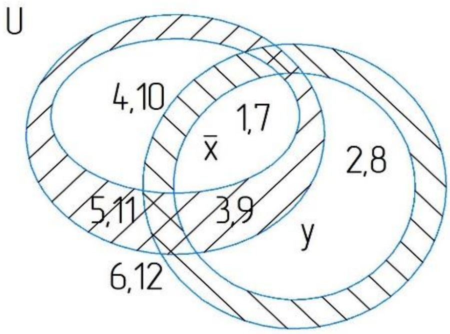


Figure 10. Graphical description of interrelation and correspondence of information situations

4. Results

A diagnosis should be made based on both a priori information about the disease and patient information. A person is involved in the diagnostic process in two distinct stages: initially, when they receive and input the initial information about the patient, and subsequently, when they participate in the final decision-making process. It is important to note that the computer system does not replace doctors; rather, it serves as a powerful tool to support the decision-making process. It presents information about the patient in an objectified, systematic form and uses knowledge of the relevant subject area for automatic diagnosis and explanation of its decision to the doctor, thus helping to avoid gross errors associated with the subjectivity of the patient’s perception. By accumulating information about patients with established diagnoses, it becomes possible to obtain objective characteristics of diagnosis and, if necessary, to retrain the computer system to enhance its accuracy. A comparison of the existing decision support methods with other methods is presented in Table 4.

Table 4. Comparison of the accuracy of decision support systems

№	Name	Average accuracy	Reference
1	Naive Bayes classifier	0.82	Jenny et al. (2015) [41]
2	Support Vector Machines	0.89	Araz et al. (2019) [42]
3	Classification And Regression Trees	0.85	Graham et al. (2018) [43]
4	Artificial neural networks	0.96	Zlotnik et al. (2016) [44]

This study analyzed the overall performance of the suboptimal approximation algorithm. The amount of non-reference data was 30% in the calculation. Simultaneously, this study presented a variety of dependencies on the number of decision search cycles with different numbers of informative correlates. Based on these data, it is possible to reveal that, as a rule, the rapid increase in volumetric and temporal obstacles is not fixed against the background of a certain level of helpful intentions and an increase in iterations. When using the developments presented in this study, the accuracy of diagnostic decisions reached 97%, which was calculated as the ratio of the correctly defined values to the total number of values, demonstrating the high efficiency of the practical use of the suboptimal approximation algorithm. The data were provided by a consortium of organizations from the Institute of Design-Technological Informatics RAS and Sechenov First Moscow State Medical University as part of a world-class medical center, as also stated in the funding. The data provided have been depersonalized and represent a list of patients with a range of symptoms (Figure 11).

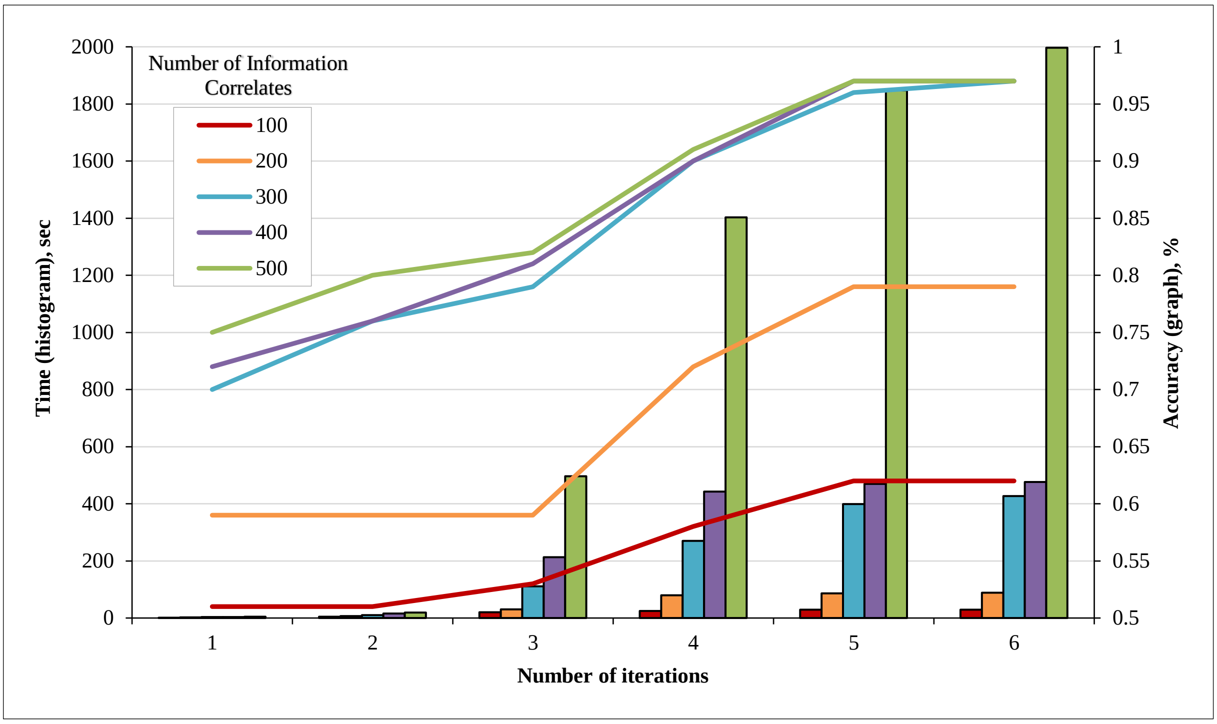


Figure 11. Demonstration of the relationship between the time and accuracy characteristics of the algorithm and the number of decision search cycles at different numbers of correlates

The proposed algorithm is capable of accurately diagnosing a given case within a relatively short period of time; however, it is not without its inherent limitations and potential drawbacks. Due to the algorithm's consideration of a multitude of states, including those of an uncertain nature, a considerable number of information correlations may have a detrimental impact on its operational speed while offering only a marginal increase in accuracy. Furthermore, the erroneous selection of algorithmic cycles may result in the expenditure of valuable time without any appreciable change in the overall accuracy of the algorithm. Machine-learning algorithms can also be implemented with the structure of non-classical logic to produce more accurate results. However, this framework has many limitations, and further development and research into hybrid algorithms are required to realize this aim.

5. Conclusion

Based on the conducted analysis, we demonstrate the potential benefits of integrating nonclassical logic with information semantics within a decision support system. Such an approach can enhance the efficiency of medical information technology. The use of frequency logic for machine representation of medical databases and internal information processing has been shown to be expedient. Trilogics and tetralogics are optimal for transferring data from doctors to automated systems. The formalism of k-value approximation logic is optimal for explaining machine decisions to doctors. A methodology for the collection and analysis of medical information utilizing the indirect address scheme was devised and deployed. The medical diagnostic process is presented as the process of the functioning of an information management system. This system receives a set of materials and informational objects as the input. These include patients, instruments, and medications. They were received together with the research results and their medical history. At the output, the system produces a set of materials and information objects. These included a healthy patient and a diagnosis. They were produced along with their appointments. This study proposes methods and algorithms for solving decision-making problems in medical diagnostic processes. These are based on optimal and suboptimal discrete-logical approximations of a priori and actual data using information and value criteria. It was demonstrated that the proposed model does not result in a linear increase in the computational complexity with the addition of new information attributes.

6. Declarations

6.1. Author Contributions

Conceptualization, L.M.C. and S.A.S.; methodology, V.Z.K.; software, I.A.A.; validation, L.M.C.; formal analysis, V.Z.K.; investigation, I.A.A.; resources, S.A.S.; data curation, L.M.C.; writing—original draft preparation, I.A.A. and L.M.C.; writing—review and editing, V.Z.K. and S.A.S.; visualization, I.A.A.; supervision, S.A.S.; project administration, L.M.C. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7. References

[1] Malmir, B., Amini, M., & Chang, S. I. (2017). A medical decision support system for disease diagnosis under uncertainty. Expert Systems with Applications, 88, 95–108. doi:10.1016/j.eswa.2017.06.031.

[2] Wan, W., Xu, J., Zeng, Q., Pan, L., & Sun, W. (2023). Development and Evaluation of Intelligent Medical Decision Support Systems. Academic Journal of Science and Technology, 8(2), 22–25. doi:10.54097/ajst.v8i2.14713.

[3] Harada, T., Miyagami, T., Kunitomo, K., & Shimizu, T. (2021). Clinical decision support systems for diagnosis in primary care: A scoping review. International Journal of Environmental Research and Public Health, 18(16), 8435. doi:10.3390/ijerph18168435.

[4] Mahfouf, M., Abbod, M. F., & Linkens, D. A. (2001). A survey of fuzzy logic monitoring and control utilisation in medicine. Artificial intelligence in medicine, 21(1-3), 27-42. doi:10.1016/S0933-3657(00)00072-5.

[5] Ahmadi, H., Gholamzadeh, M., Shahmoradi, L., Nilashi, M., & Rashvand, P. (2018). Diseases diagnosis using fuzzy logic methods: A systematic and meta-analysis review. Computer Methods and Programs in Biomedicine, 161, 145–172. doi:10.1016/j.cmpb.2018.04.013.

[6] Steen, A., & Benzmüller, C. (2024). Challenges for Non-Classical Reasoning in Contemporary AI Applications. Kunstliche Intelligenz, 38, 7-16. doi:10.1007/s13218-024-00855-8.

[7] Boulila, W., Farah, I. R., & Hussain, A. (2018). A novel decision support system for the interpretation of remote sensing big data. Earth Science Informatics, 11(1), 31–45. doi:10.1007/s12145-017-0313-7.

[8] Kose, U., Deperlioglu, O., Alzubi, J., & Patrut, B. (2021). Deep Learning for Medical Decision Support Systems. Studies in Computational Intelligence. Springer, Singapore. doi:10.1007/978-981-15-6325-6.

[9] Todd, P., & Benbasat, I. (1999). Evaluating the Impact of DSS, Cognitive Effort, and Incentives on Strategy Selection. Information Systems Research, 10(4), 356–374. doi:10.1287/isre.10.4.356.

[10] Chen, Z., Liang, N., Zhang, H., Li, H., Yang, Y., Zong, X., Chen, Y., Wang, Y., & Shi, N. (2023). Harnessing the power of clinical decision support systems: Challenges and opportunities. Open Heart, 10(2), 2432. doi:10.1136/openhrt-2023-002432.

[11] Schaaf, J., Sedlmayr, M., Schaefer, J., & Storf, H. (2020). Diagnosis of Rare Diseases: a scoping review of clinical decision support systems. Orphanet Journal of Rare Diseases, 15(1), 263. doi:10.1186/s13023-020-01536-z.

[12] Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: benefits, risks, and strategies for success. NPJ Digital Medicine, 3, 17. doi:10.1038/s41746-020-0221-y.

[13] Almazroi, A. A., Aldhahri, E. A., Bashir, S., & Ashfaq, S. (2023). A Clinical Decision Support System for Heart Disease Prediction Using Deep Learning. IEEE Access, 11, 61646–61659. doi:10.1109/ACCESS.2023.3285247.

[14] Miyachi, Y., Ishii, O., & Torigoe, K. (2023). Design, implementation, and evaluation of the computer-aided clinical decision support system based on learning-to-rank: collaboration between physicians and machine learning in the differential diagnosis process. BMC Medical Informatics and Decision Making, 23(1), 26. doi:10.1186/s12911-023-02123-5.

[15] Chen, M., Cui, D., Haick, H., & Tang, N. (2024). Artificial Intelligence- Based Medical Sensors for Healthcare System. Advanced Sensor Research, 3(3), 2300009. doi:10.1002/adsr.202300009.

[16] Nilius, H., Cuker, A., Haug, S., Nakas, C., Studt, J. D., Tsakiris, D. A., Greinacher, A., Mendez, A., Schmidt, A., Wuillemin, W. A., Gerber, B., Kremer Hovinga, J. A., Vishnu, P., Graf, L., Kashev, A., Sznitman, R., Bakchoul, T., & Nagler, M. (2023). A machine-learning model for reducing misdiagnosis in heparin-induced thrombocytopenia: A prospective, multicenter, observational study. EClinicalMedicine, 55, 101745. doi:10.1016/j.eclinm.2022.101745.

[17] Tatarkanov, A., Lampezhev, A., Polezhaev, D., & Tekeev, R. (2022). Suboptimal Biomedical Diagnostics in the Presence of Random Perturbations in the Data. International Journal of Engineering Trends and Technology, 70(11), 129–137. doi:10.14445/22315381/IJETT-V70I11P213.

[18] Pumplun, L., Fecho, M., Wahl, N., Peters, F., & Buxmann, P. (2021). Adoption of machine learning systems for medical diagnostics in clinics: Qualitative interview study. Journal of Medical Internet Research, 23(10), 29301. doi:10.2196/29301.

[19] Tatarkanov, A. A., Umyskov, A. A., Tekeev, R. K., & Kuklin, V. Z. (2022). Model Development of Universal Hardware and Software Module for Medical Information System. International Journal of Emerging Technology and Advanced Engineering, 12(10), 136–146. doi:10.46338/ijetae1022_15.

[20] Kukhtevich, I. I., Goryunova, V. V., Goryunova, T. I., & Zhilyaev, P. S. (2020). Medical Decision Support Systems and Semantic Technologies in Healthcare. Russian Conference on Digital Economy and Knowledge Management, 370–375. doi:10.2991/aebmr.k.200730.068.

[21] Andrade, S. E., Kahler, K. H., Frech, F., & Chan, K. A. (2006). Methods for evaluation of medication adherence and persistence using automated databases. Pharmacoepidemiology and Drug Safety, 15(8), 565–574. doi:10.1002/pds.1230.

[22] Knapič, S., Malhi, A., Saluja, R., & Främling, K. (2021). Explainable Artificial Intelligence for Human Decision Support System in the Medical Domain. Machine Learning and Knowledge Extraction, 3(3), 740–770. doi:10.3390/make3030037.

[23] Groenier, M., Pieters, J. M., Witteman, C. L. M., & Lehmann, S. R. S. (2014). The effect of client case complexity on clinical decision-making. European Journal of Psychological Assessment, 30(2), 150–158. doi:10.1027/1015-5759/a000184.

[24] Tyapkin, V. N., Ishchuk, I. N., Kabulova, E. G., Semenov, M. E., & Meleshenko, P. A. (2016). Singular spectral analysis in filtration of noisecontaminated signals of pseudolite navigation. Indian Journal of Science and Technology, 9(46), 107567. doi:10.17485/ijst/2016/v9i46/107567.

[25] Starke, S. D., & Baber, C. (2020). The effect of known decision support reliability on outcome quality and visual information foraging in joint decision-making. Applied Ergonomics, 86, 103102. doi:10.1016/j.apergo.2020.103102.

[26] Bussone, A., Stumpf, S., & O'Sullivan, D. (2015). The role of explanations on trust and reliance in clinical decision support systems. Proceedings - 2015 IEEE International Conference on Healthcare Informatics, 160–169. doi:10.1109/ICHI.2015.26.

[27] Yan, H., Jiang, Y., Zheng, J., Peng, C., & Li, Q. (2006). A multilayer perceptron-based medical decision support system for heart disease diagnosis. Expert Systems with Applications, 30(2), 272-281. doi:10.1016/j.eswa.2005.07.022.

[28] Vinodh, S., & Balaji, S. R. (2011). Fuzzy logic based leanness assessment and its decision support system. International Journal of Production Research, 49(13), 4027–4041. doi:10.1080/00207543.2010.492408.

[29] Akishev, K. M., Zhamangarin, D. S., Zhardemkyzy, S., Murzabekov, T. T., Nurgaliyev, A. Y., & Zhiganbayev, M. Y. (2023). Application of the Principle of Special States in Developing Simulation Model. News of the National Academy of Sciences of the Republic of Kazakhstan, Series of Geology and Technical Sciences, 1(457), 33–44. doi:10.32014/2023.2518-170X.257.

[30] Mark, D. B., & Wong, J. B. (2005). Decision-making in clinical medicine. Harrisons Principles of Internal Medicine, 16(1), 6.

[31] Coussement, K., Benoit, D. F., & Antioco, M. (2015). A Bayesian approach for incorporating expert opinions into decision support systems: A case study of online consumer-satisfaction detection. Decision Support Systems, 79, 24–32. doi:10.1016/j.dss.2015.07.006.

[32] Barbini, E., Manzi, P., & Barbini, P. (2013). Bayesian Approach in Medicine and Health Management. Current Topics in Public Health, IntechOpen, London, United Kingdom. doi:10.5772/52402.

[33] Delen, D., & Sharda, R. (2008). Artificial Neural Networks in Decision Support Systems. Handbook on Decision Support Systems 1. Springer, Heidelberg, Germany. doi:10.1007/978-3-540-48713-5_26.

[34] Haque, M. T., & Kashtiban, A. M. (2005). Application of neural networks in power systems; A review. Proceedings - WEC 05: Fourth World Enformatika Conference, 6, 53–57.

[35] Liu, Y., Ren, Z. H., Li, D. M., Tian, X. K., & Lu, Z. N. (2006). The research of precision irrigation decision support system based on genetic algorithm. Proceedings of the 2006 International Conference on Machine Learning and Cybernetics, 2006, 3123–3127. doi:10.1109/ICMLC.2006.258403.

[36] Ocak, H. (2013). A medical decision support system based on support vector machines and the genetic algorithm for the evaluation of fetal well-being. Journal of Medical Systems, 37(2), 1-9. doi:10.1007/s10916-012-9913-4.

[37] Babcock, B., Babu, S., Datar, M., Motwani, R., & Widom, J. (2002). Models and issues in data stream systems. Proceedings of the ACM SIGACT-SIGMOD-SIGART Symposium on Principles of Database Systems, 1–16. doi:10.1145/543613.543615.

[38] Tatarkanov, A. A., Alexandrov, I. A., Chervjakov, L. M., & Karlova, T. V. (2022). A Fuzzy Approach to the Synthesis of Cognitive Maps for Modeling Decision Making in Complex Systems. Emerging Science Journal, 6(2), 368–381. doi:10.28991/ESJ-2022-06-02-012.

[39] Davis, R. (1977). A DSS for diagnosis and therapy. ACM SIGMIS Database, 8(3), 58–72. doi:10.1145/1017583.1017597.

[40] Dujmović, J. J. (2007). Continuous preference logic for system evaluation. IEEE Transactions on Fuzzy Systems, 15(6), 1082–1099. doi:10.1109/TFUZZ.2007.902041.

[41] Jenny, M. A., Hertwig, R., Ackermann, S., Messmer, A. S., Karakoumis, J., Nickel, C. H., & Bingisser, R. (2015). Are mortality and acute morbidity in patients presenting with nonspecific complaints predictable using routine variables? Academic Emergency Medicine, 22(10), 1155–1163. doi:10.1111/acem.12755.

[42] Araz, O. M., Olson, D., & Ramirez-Nafarrate, A. (2019). Predictive analytics for hospital admissions from the emergency department using triage information. International Journal of Production Economics, 208, 199–207. doi:10.1016/j.ijpe.2018.11.024.

[43] Graham, B., Bond, R., Quinn, M., & Mulvenna, M. (2018). Using Data Mining to Predict Hospital Admissions from the Emergency Department. IEEE Access, 6, 10458–10469. doi:10.1109/ACCESS.2018.2808843.

[44] Zlotnik, A., Alfaro, M. C., Perez, M. C. P., Gallardo-Antolin, A., & Martinez, J. M. M. (2016). Building a Decision Support System for Inpatient Admission Prediction with the Manchester Triage System and Administrative Check-in Variables. CIN - Computers Informatics Nursing, 34(5), 224–230. doi:10.1097/CIN.0000000000000230.