Available online at: https://ijact.in

Date of Submission	21/04/2019
Date of Acceptance	29/05/2019
Date of Publication	30/06/2019
Page numbers	3158-3165(8 Pages)

Cite This Paper: AK Nishanov, GP Djurayev, Malika A Khasanova.(2019) Improved algorithms for calculating evaluations in processing medical data, 8(6), COMPUSOFT, An International Journal of Advanced Computer Technology. PP. 3158-3165.

ISSN:2320-0790

An International Journal of Advanced Computer Technology

IMPROVED ALGORITHMS FOR CALCULATING EVALUATIONS IN PROCESSING MEDICAL DATA

Prof. Akhram Khasnovich Nishanov[1], Gulomjon Primovich Djurayev[2], Malika Akhramovna Khasanova[3]

[1]Department of Information Technology Software, [2]Independent researcher of the Scientific Innovation Center
[3]Assistant of the Department of Hospital Therapy of Faculty No. 2
[1,2]Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Uzbekistan
[3]Tashkent Medical Academy, Uzbekistan

Abstract: The paper examines the issues of diagnosis and treatment of cardiovascular diseases, commonly encountered in diagnostic decision-making, when medical data are processed. The issues of classification of heart diseases and detection of informative signs are solved on the basis of estimation algorithms. In addition, the appropriate software was developed.
The main goal of the research is to solve such issues as constructing inter-object remoteness in a complex of informative features that distinguish objects of diagnostic classes, select a complex of signs that characterize mutual differences of objects, and also identify the value of the proximity function when diagnosing an unknown object [1-5].
The level of significance or representation of the set belonging to the j-object ofX_p-class, which are the main stages of the algorithms for calculating its assessment relative to the class [1-5], was revealed.
An algorithm for diagnosing an unknown object in the space of informative features was proposed. The suggested theoretical ideas were confirmed in practice. In addition, the decision rules in this space and their software were developed [4-5].

Keywords: pattern recognition, remoteness and proximity functions, estimation algorithms, classification, informative features.

I. INTRODUCTION

In determining the patterns and hidden intercomplex dependencies of the signs and those that characterize the objects of research in solving the problems of the intellectual analysis of medical data, measurement and spatial problems arise. As a rule, the measurement of medical data that are collected and stored consists of dozens or hundreds of signs. The decision-making process based on these data becomes a very complex one for specialists. Therefore, the urgent issues of the modern health care system is the transition from large quantities to small, but informative ones in processing medical data, i.e. identifying the most important information; developing software based on the methods and algorithms for classification of attributes.

One of the immediate problems of the present moment is the analysis of issues of pattern recognition in the data mining environment and the introduction of methods and algorithms for solving such problems, the results obtained in all production fields. Scientists who conducted long-term research in applied mathematics, computer science and information and communication technologies are specialists in this field. A review of the results of their analytical work on pattern recognition and in-depth study of the proposed provisions were reflected in the following works [1-5, 7, 9, 13]. Models based on estimation, mathematical statistics, probability theory, potentials and pattern recognition based on the obtained results were studied.

The results of the analysis of these models revealed the absence of interdependencies between important features or the presence of very loose coupling.

Pattern recognition algorithms created on the basis of the models proposed in some scientific papers [1-5, 7, 9, 13] are inextricably linked with an increase in the number of learning samples, which in turn implies performing a large number of calculations. This implies stepping up the requirements imposed by researchers on technical means.

Thus, it is relevant to develop models, methods and algorithms that take into account the features of the object of study when processing large amounts of data [6, 8, 10-12].

The main objective of this paper is to develop an improved algorithm for estimation in the mining of medical data considered in the space of a set of features [6, 8, 10-12], as well as its implementation in solving three issues of image transformation.

II. METHOD AND MATERIAL

In this section: 1). The features of preliminary data processing, which are expressed on the example of medical issues, are described. In this section, three tasks are considered: the first is the selection of informative features that are the basis of pattern recognition, the second is the determination of the significance level of objects of an learning sample, the third is diagnosis, which is the main medical issue; 2). The methods of solving the objectives, which include the remoteness function with respect to two objects in the space of Boolean informative features and the proximity function, providing the similarity of objects are defined. The mathematical expression of decision rules determining diagnoses is described in the same way; 3). Algorithms for solving the set objectives are developed on the basis of the proposed theoretical information; 4). The proposed algorithm is implemented in the solution of a practical problem. At step-by-step solution of the set objectives on the basis of symptoms for the class of homogeneous diseases 'Myocardial infarction'and the corresponding diagnoses in the form of a table were described.

1. Layout of the case. Let us assume that, as in [1-5] literature, the selection of educational choices is given:$x_{p1}, x_{p2}, \dots, x_{pm_p} \in X_p, p = \overline{1,r}$. Here x_{pi} - N - dimensional space vector, each object$x_{pi} = (x_{pi}^1,$ $xpi2, \dots xpiN, i{=}1, mp,$ N - dimensional features in space, X_p, $p = \overline{1,r}$ representing a sequence of classes that consists of, the$m_p$is$x_{p1}, \dots, x_{p_{m_p}}$.

Issue: 1. It is required to identify a set of informative features that clearly distinguish between class X_p diseases.

Issue: 2. It is necessary to evaluate the contribution of X_p class objects to the formation of their class.

Issue: 3 - Establishing a decisive rule for identifying an object that is identical to a class in the diagnosis of an illness.

2. Methods for Solving the Set Objectives

In order to solve the problem, the following finds include the proximity function of the two objects, the distance function that provides the difference, and the similarity between objects and class objects.

Likewise, the function of calculating the votes counting the contribution of class objects to the formation of their class is based on estimate calculationalgorithmalgorithms [1-4]

Distant function in the field of information feature:

Let's assume that the $X_p$class of information feature is given by two x_{p1}, x_{p2} objects.

The distance function between objects is to enter $\theta_i(x_{p1,}x_{p2})$ in the following informative features:

$$\sigma_i(x_{p1,}x_{p2}) = \begin{cases} 1 \quad if \qquad (x_{p1}^i - x_{p2}^i) \neq 0, i = \overline{1,N}. \\ 0 \text{ otherwise } (x_{p1}^i - x_{p2}^i) = 0, i = \overline{1,N}. \end{cases} \quad (1)$$

The first condition indicates that there are no similarities between the two objects, and the second condition indicates their similarity.

Proximity functions in the field of informative features.

Let's assume that the $X_p$class of information feature is given by two x_{p1}, x_{p2} objects.

The proximity function between the objects $\rho_i(x_{p1,}x_{p2})$ is found in the following informative features:

$$\rho_i(x_{p1,}x_{p2}) = \begin{cases} 1 \quad \text{if} \qquad (x_{p1}^i - x_{p2}^i) = 0, i = \overline{1,N}. \\ 0 \qquad\qquad\qquad\qquad \text{otherwise,} \end{cases} \quad (2)$$

The first condition indicates the degree of similarity between the two objects, and the second condition indicates that they are different from each other, meaning that these components are not identical.

This is a voluntary j - in the field of informative signs, is based on the formula for the measurement of the size, which represents the difference between the diagnostic object and all other diagnostic objects.

$$\Gamma_j(x_{pj,}x_{pk}) = \sum_{\kappa=1}^{m_p} \sum_{i=1}^{N} \theta_i(x_{pj,}x_{pk}), j = \overline{1,m_p};\ k = \overline{1,m_p};\ j \neq k. \quad (3)$$

In the field of information featureistic, the value of j-object's contribution to the diagnostic object is calculated based on the following formula:

$$\Gamma_j\left(x_{pj},x_{pk}\right)=\sum_{\kappa=1}^{m_p}\sum_{i=1}^{N}\rho_i\left(x_{pj},x_{pk}\right),j=\overline{1,m_p};\ k=\overline{1,m_p};\ j\neq k. \quad (4)$$

A crucial rule in the field of informative features [4-6].

Let's assume that the new unknownw=(w^1,w^2,…,w^N) is given to the diagnostic object. This object is most similar to the one given to the diagnostic object.

$$\Gamma_w\left(w,x_{pk}\right)=\sum_{\kappa=1}^{m_p}\sum_{i=1}^{N}\rho_i\left(w,x_{pk}\right),k=\overline{1,m_p};, \quad (5).$$

is calculated by the formula. If $\Gamma_w\left(w,x_{pi},\right)>\Gamma_w\left(w,x_{pj},\right)$ (6) inequality is achieved, then w=(w^1,w^2,…,w^N) is relatively high for the i-diagnostic object relative to others.

3. Algorithm for solving issues.

This chapter outlines the algorithm for solving the issues that are described in the article. The algorithm consists of six paragraphs and it is desirable to use logic identification only for separate class objects.

The first step. The curriculum selection objects are included in the database. The initial database is formed in allX_p, $p=\overline{1,r}$ classes;

The second step. In the field of information featureistic of determining the complex of informative features, which distinguishes between X_p class diseases, the distance function is calculated according to formula (1);

The third step. The area of informative featureistic used to estimate the contribution of the X_p classes to the formation of their class is the proximity function (2) according to the formula;

The fourth step. This is the optional criterion in the field of informative signs - an assessment of the magnitude of the difference between the diagnostic object and all other diagnostic objects is based on the formula (3);

The fifth step. In the information feature space, the assessment of the contribution of j-object to the class of objects is carried out under the formula (4);

The sixth step. The key determining factor for identifying an object that is unknown to the illness, i.e. the subject of the class, is built on the basis of the formula (5, 6).

4. Applying proposed algorithm in determining the solution of a practical problem.

Let us present the symptoms and the corresponding diagnoses for the class of homogeneous diseases (CHD) 'Myocardial infarction' in the form of a table (table No. 1). Inline elements of the table express diagnoses; elements of the columns indicate signs.

Thus, the space of diagnoses and signs defined for the class of these diseases is formed on the basis of the experience of specialists and industry experts and consists of 8 diagnoses and 23 signs characterizing each diagnosis.

Table: 1

№	Symptoms	Diagnoses							
		Miocard(T_1)	Pericarditis (T_2)	Miocarditis (T_3)	Aortic Aneurysm (T_4)	Pevmotorox (T_5)	Thromboembolism of the lung artery (TLA) ($_6$)	Acute cholecystitis (T_7)	Myocardial infarction (T_8)
1.	Infringement of heart rhythm (y_1)	1	1	1	1	0	0	0	1
2.	Arterial blood pressure increase (y_2)	1	0	0	1	1	0	0	1
3.	Pericardial rubbing noise (y_3)	1	1	0	0	0	0	0	0
4.	ECG changes (y_4)	1	1	1	0	0	1	0	1
5.	Pain in the heart (y_5)	1	1	1	1	1	1	0	0
6.	Increase in body temperature (y_6)	1	1	0	0	0	0	1	0
7.	Leucocytosis (y_7)	1	1	0	0	0	0	1	0
8.	Heart Tones Collapse (y_8)	1	1	1	1	1	1	0	1
9.	ST segment rise (y_9)	0	1	1	0	0	0	0	0
10.	The appearance of the Q tumor (y_{10})	1	0	1	0	0	0	0	1
11.	ST segment elevation or depression (y_{11})	1	1	0	1	0	0	0	0
12.	ST segment and spinal cord changes (y_{12})	0	0	0	1	0	0	1	0
13.	Slow change of K spike from V1 to V6 (y_{13})	1	0	0	0	1	0	0	0
14.	Sudden changes in the heartbeat (y_{14})	1	0	0	1	1	1	0	0
15.	ST segment II, III, aVF rise (y_{15})	1	0	0	0	0	1	1	0
16.	T in V1-V3 inversion (y_{16})	1	0	0	0	0	1	0	0
17.	After 8-10 hours, the increase in the CFK and MV fractions (y_{17})	1	0	1	0	0	0	0	0
18.	Return of the CFK and MV fractions after 48-72 hours (y_{18})	1	0	0	0	0	0	0	0
19.	After 24-36 hours activation of the CFK and MV fractions (y_{19})	1	0	0	0	0	0	0	0
20.	Local disturbance of left ventricular retraction (y_{20})	1	0	0	0	0	0	1	1
21.	Left ventricular wall decline (y_{21})	1	0	1	0	0	0	0	1
22.	Normal ablation of left ventricle (y_{22})	0	0	0	0	0	0	0	0
23.	Trompoe oceanography of the Koranar artery (y_{23})	1	0	0	0	0	0	0	1

The following issues need to be addressed:

1. Determine the sequence of informative features that are clearly distinguishable among class X_p diseases.

2. Assessment of contribution of X_p class objects to formation of their class.

3. Establish a decisive rule for the identification of an object that is identical to a class in the diagnosis of an illness.

The first and second issues are solved in the following stages:

First stage: Based on Table №1, the following T matrix is:

$$\textbf{formed:}T=\begin{pmatrix} & y_1 & y_2 & y_3 & y_4 & y_5 & y_6 & y_7 & y_8 & y_9 & y_{10} & y_{11} & y_{12} & y_{13} & y_{14} & y_{15} & y_{16} & y_{17} & y_{18} & y_{19} & y_{20} & y_{21} & y_{22} & y_{23} \\ T_1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ T_2 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_3 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ T_4 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_5 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_6 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_7 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ T_8 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \end{pmatrix}$$

Elements of the matrix are the objects of diagnosis, and column elements are the symbols of the objects.

The second step is the distances function between objects $\theta_i\left(y_{\text{т}k,}y_{\text{т}i}\right), i = \overline{2,8;}, , j = \overline{1,23;,}\;\; k = \overline{1,8;}, , j \neq k;$.Using the T matrix:

$$T_{T_1}=\begin{pmatrix} & y_1 & y_2 & y_3 & y_4 & y_5 & y_6 & y_7 & y_8 & y_9 & y_{10} & y_{11} & y_{12} & y_{13} & y_{14} & y_{15} & y_{16} & y_{17} & y_{18} & y_{19} & y_{20} & y_{21} & y_{22} & y_{23} \\ T_2: & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ T_3: & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 1 \\ T_4: & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ T_5: & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ T_6: & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ T_7: & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 \\ T_8: & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \end{pmatrix}$$

One of the main functions of the distance function$\theta_i\left(y_{\text{т}k,}y_{\text{т}i}\right)$ is the operator, ie. (1) the expression T. matrix and T_{T_1} matrix when the T1 is applied to the diagnostic object. The resulting matrix T1 is understood as a comparative matrix for the diagnostic object. Comparative matrices are defined as $T_{T_i}$and $T_i$is a comparative matrix for the diagnostic object, and T_i is evaluated comparatively with the diagnosis.

1. The T_{T_1} matrix for the comparative assessment is based on the path and column elements of the matrix:

When evaluating the matrix within the path elements,T_i is the sum of the differences in the parameters of the object of the diagnostic, ie, T_j, $i \neq j$, (in our case T_1), which is relative to the diagnostic object, ie the sum of the matrix elements: $\Gamma\left(T_{T_1}\right) = \Gamma_1\left(y_{\text{т}1,}y_{\text{т}2}\right) + \Gamma_1\left(y_{\text{т}1,}y_{\text{т}3}\right) + \cdots + \Gamma_1\left(y_{\text{т}1,}y_{\text{т}8}\right) = 13 + 14 + 15 + 15 + 14 + 17 + 12 = 100$. The average value of the price is$\overline{\Gamma}\left(T_{T_1}\right) = \frac{1}{7}\Gamma\left(T_{T_1}\right) = 14{,}3$

2. The evaluation is the sum of the columns in the column of the element of the matrix. This means the T_1 identifier of the diagnostic object is of a comparative degree of importance compared to the diagnostic objects $T_i, i = \overline{2,8}$. As a result of this evaluation, a set of informative features is defined for two diagnostic objects. The most informative feature is the sum of the sum of the column elements in the largest value. The two most informative features are the sum of the two columns of the matrix and the largest.

This rating consists of a set of informative features for a T_1 diagnostic object, as follows: Y3, Y6, Y7, Y10, Y11, Y13, Y15, Y16, Y17, Y18, Y19,Y20, Y21, Y23.

Here are lists of 14 informative brands.

Likewise, the T_2 class of comparative assessment is as follows:

$$T_{T_2}=\begin{pmatrix} & y_1 & y_2 & y_3 & y_4 & y_5 & y_6 & y_7 & y_8 & y_9 & y_{10} & y_{11} & y_{12} & y_{13} & y_{14} & y_{15} & y_{16} & y_{17} & y_{18} & y_{19} & y_{20} & y_{21} & y_{22} & y_{23} \\ T_1: & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ T_3: & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ T_4: & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_5: & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_6: & 1 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_7: & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ T_8: & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \end{pmatrix}$$

Here T_2 assessment is carried out as follows: $\Gamma\left(T_{T_2}\right) = \Gamma_2\left(x_{\text{т}2,}x_{\text{т}1}\right) + \Gamma_2\left(x_{\text{т}2,}x_{\text{т}3}\right) + \cdots + \Gamma_2\left(x_{\text{т}2,}x_{\text{т}8}\right)$ = 13 + 7 + 8 + 10 + 9 + 10 + 11=68. Average value is equal to $\overline{\Gamma}\left(T_{T_2}\right)$=9,7 Similarly, a column of elements, that is, a set of informative features, is as follows: Y3, Y6, Y7, Y9, Y11.

There are 5 informative brands required:

$$T_{T_8}=\begin{pmatrix} & y_1 & y_2 & y_3 & y_4 & y_5 & y_6 & y_7 & y_8 & y_9 & y_{10} & y_{11} & y_{12} & y_{13} & y_{14} & y_{15} & y_{16} & y_{17} & y_{18} & y_{19} & y_{20} & y_{21} & y_{22} & y_{23} \\ T_1: & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ T_2: & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ T_3: & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ T_4: & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ T_5: & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ T_6: & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ T_7: & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \end{pmatrix}$$

Matrix view is held.

Here T_8 is evaluated as follows: $\Gamma\left(T_{T_8}\right) = \Gamma_8\left(x_{\text{т}8,}x_{\text{т}1}\right) + \Gamma_8\left(x_{\text{т}8,}x_{\text{т}2}\right) + \cdots + \Gamma_8\left(x_{\text{т}8,}x_{\text{т}7}\right) = 12 + 11 + 6 + 9 + 9 + 10 + 11 = 68.$

Average value is equal to $\overline{\Gamma}\left(T_{T_8}\right) = 9{,}7$. The set of informative features is selected as follows:Y5, Y10, Y20, Y21, Y23.

The results obtained at the end of the stage are shown in Table №2, Table№3, Table№4

Table: 2

$\Gamma(T_{T_1})$	$\Gamma(T_{T_2})$	$\Gamma(T_{T_3})$	$\Gamma(T_{T_4})$	$\Gamma(T_{T_5})$	$\Gamma(T_{T_6})$	$\Gamma(T_{T_7})$	$\Gamma(T_{T_8})$
100	68	66	62	62	62	80	68
$\overline{\Gamma}(T_{T_1})$	$\overline{\Gamma}(T_{T_2})$	$\overline{\Gamma}(T_3)$	$\overline{\Gamma}(T_{T_4})$	$\overline{\Gamma}(T_{T_5})$	$\overline{\Gamma}(T_{T_6})$	$\overline{\Gamma}(T_{T_7})$	$\overline{\Gamma}(T_{T_8})$
14,3	9,7	9,4	8,9	8,9	8,9	11,4	9,7

Table: 3

	y_1	y_2	y_3	y_4	y_5	y_6	y_7	y_8	y_9	y_{10}	y_{11}	y_{12}	y_{13}	y_{14}	y_{15}	y_{16}	y_{17}	y_{18}	y_{19}	y_{20}	y_{21}	y_{22}	y_{23}
T_1	3	4	6	3	2	5	5	1	2	5	5	2	6	4	5	6	6	7	7	5	5	0	6
T_2	3	4	6	3	2	5	5	1	6	3	5	2	2	4	3	2	2	1	1	3	3	0	2
T_3	3	4	2	3	2	3	3	1	6	5	3	2	2	4	3	2	6	1	1	3	5	0	2
T_4	3	4	2	5	2	3	3	1	2	3	5	6	2	4	3	2	2	1	1	3	3	0	2
T_5	5	4	2	5	2	3	3	1	2	3	3	2	6	4	3	2	2	1	1	3	3	0	2
T_6	5	4	2	3	2	3	3	1	2	3	3	2	2	4	5	6	2	1	1	3	3	0	2
T_7	5	4	2	5	6	5	5	7	2	3	3	6	2	4	5	2	2	1	1	5	3	0	2
T_8	3	4	2	3	6	3	3	1	2	5	3	2	2	4	3	2	2	1	1	5	5	0	6

The range of informative T_i- signs important for diagnostic objects is shown in Table №4.

№	Diagnoses	Informative Features
1.	$\mathbf{T_1}$	$Y_3, Y_6, Y_7, Y_{10}, Y_{11}, Y_{13}, Y_{15}, Y_{16}, Y_{17}, Y_{18}, Y_{19}, Y_{20}, Y_{21}, Y_{23}$
2.	$\mathbf{T_2}$	$Y_3, Y_6, Y_7, Y_9, Y_{11}$
3.	$\mathbf{T_3}$	$Y_9, Y_{10}, Y_{17}, Y_{21}$
4.	$\mathbf{T_4}$	Y_4, Y_{11}, Y_{12}
5.	$\mathbf{T_5}$	Y_1, Y_4, Y_{13}
6.	$\mathbf{T_6}$	Y_1, Y_{15}, Y_{16}
7.	$\mathbf{T_7}$	$Y_1, Y_4, Y_5, Y_6, Y_7, Y_8, Y_{12}, Y_{15}, Y_{20}$
8.	$\mathbf{T_8}$	$Y_5, Y_{10}, Y_{20}, Y_{21}, Y_{23}$

Solution for the third issue: Let us suppose that we give an optional W unknown diagnosis to an object. Parameters of this object are obtained in relation to the parameters of the type $T_i$of Table №1 and describe the following matrix shape.

$$W = (0\,0\,1\,0\,1\,1\,0\,0\,0\,1\,1\,0\,1\,0\,1\,1\,1\,1\,1\,1\,1\,0\,1)$$

Algorithm for solving applied problems.

Step 1: Based on the parameters of Table №1 and W of the unknown diagnostic object, we create the P class in the form of a matrix:

$$P= \begin{array}{c|ccccccccccccccccccccccc} & y_1 & y_2 & y_3 & y_4 & y_5 & y_6 & y_7 & y_8 & y_9 & y_{10} & y_{11} & y_{12} & y_{13} & y_{14} & y_{15} & y_{16} & y_{17} & y_{18} & y_{19} & y_{20} & y_{21} & y_{22} & y_{23} \\ \hline T_1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ T_2 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_3 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ T_4 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_5 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_6 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_7 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ T_8 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ W & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \end{array}$$

The path elements of the P matrix are the diagnostic objects and column elements are the symbols of the objects.

Step 2: P-matrix $T_1$is an identifying mark for the disease type (table №4) $y_3, y_6, y_7, y_{10}, y_{11}, y_{13}, y_{15}, y_{16}, y_{17}, y_{18}, y_{19}, y_{20}, y_{21}, y_{23}$; the columns are separated and the remainder are discarded.The resulting matrix is T_1, a matrix for the type of disease, and separates the columns labeled P_{T_1} and the remainder is abandoned.

$$P_{T_1} = \begin{array}{c|cccccccccccccc} & y_3 & y_6 & y_7 & y_{10} & y_{11} & y_{13} & y_{15} & y_{16} & y_{17} & y_{18} & y_{19} & y_{20} & y_{21} & y_{23} \\ \hline T_1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ T_2 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_3 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ T_4 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_5 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_6 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_7 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ T_8 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ W & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{array}$$

Function of the proximity between objects $p_i\left(y_w, y_{T_i}\right), i = \overline{1,8;}$ using P_{T_1} matrix:

$$P_{T_1}(W) = \begin{array}{c|cccccccccccccc} & y_3 & y_6 & y_7 & y_{10} & y_{11} & y_{13} & y_{15} & y_{16} & y_{17} & y_{18} & y_{19} & y_{20} & y_{21} & y_{23} \\ \hline T_1: & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ T_2: & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_3: & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ T_4: & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_5: & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_6: & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ T_7: & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ T_8: & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \end{array}$$

One of the main functions of the proximity function $p_i(y_w, y_{T_i})$ is the operatorship, i.e. (1) the expression P_{T_1} in the matrix, and the result is shown on the $P_{T_1}(W)$ matrix it is read as a comparative matrix.

When the $P_{T_1}(W)$ computed matrix is computed as a linear element, then T_i is the sum of the differences in the parameters of the object of the diagnostic object (ieT_1), which is relative to the unknown object W, ie the sum of the matrix elements: $\Gamma_w\left(P_{T_1}\right) = \Gamma_1\left(y_w, y_{T_1}\right) + \Gamma_1\left(y_w, y_{T_2}\right) + \cdots + \Gamma_1\left(y_w, y_{T_8}\right) = 13 + 3 + 4 + 2 + 2 + 3 + 3 + 5 = 35.$

Step 3: P-matrix $T_2 -$ the informative signs detected for the disease type (table №4) $y_3, y_6, y_7, y_9, y_{11}$; the columns are separated and the remainder are discarded. The resulting matrix is $T_2 -$ called matrix, and we call it P_{T_2}.

$$P_{T_2} = \begin{array}{c|ccccc} & y_3 & y_6 & y_7 & y_9 & y_{11} \\ \hline T_1 & 1 & 1 & 1 & 0 & 1 \\ T_2 & 1 & 1 & 1 & 1 & 1 \\ T_3 & 0 & 0 & 0 & 1 & 0 \\ T_4 & 0 & 0 & 0 & 0 & 1 \\ T_5 & 0 & 0 & 0 & 0 & 0 \\ T_6 & 0 & 0 & 0 & 0 & 0 \\ T_7 & 0 & 1 & 1 & 0 & 0 \\ T_8 & 0 & 0 & 0 & 0 & 0 \\ W & 1 & 1 & 0 & 0 & 1 \end{array}$$

The proximity function between objects is $p_i(y_w, y_{T_i}), i = \overline{1,8};$ using P_{T_2} matrix

$$P_{T_2}(W) = \left(\begin{array}{cccccc} & y_3 & y_6 & y_7 & y_9 & y_{11} \\ T_1: & 1 & 1 & 0 & 1 & 1 \\ T_2: & 1 & 1 & 0 & 0 & 1 \\ T_3: & 0 & 0 & 1 & 0 & 0 \\ T_4: & 0 & 0 & 1 & 1 & 1 \\ T_5: & 0 & 0 & 1 & 1 & 0 \\ T_6: & 0 & 0 & 1 & 1 & 0 \\ T_7: & 0 & 1 & 0 & 1 & 0 \\ T_8: & 0 & 0 & 1 & 1 & 0 \end{array}\right)$$

When $P_{T_2}(W)$ is generated within the linear elements of the matrix, the value of the difference in the parameters of the diagnostic object T_i (ie, T_2), which is relative to the unknown object W, is the sum of the matrix elements: $\Gamma_w(P_{T_2}) = \Gamma_2(y_w, y_{T_1}) + \Gamma_2(y_w, y_{T_2}) + \cdots + \Gamma_2(y_w, y_{T_8}) = 4 + 3 + 1 + 3 + 2 + 2 + 2 + 2 = 19.$

In the same manner, fromP-matrix,T_3, T_4 ... etc. is calculated for types of diseases, and forT_8, it is calculated is follows.

Step 9: P-matrix T_8 -information signs for the type of illness (table №4) $y_5, y_{10}, y_{20}, y_{21}, y_{23}$; the columns are separated and the remainder are discarded. The resulting matrix is T_8, and we call it P_{T_8}.

$$P_{T_8} = \left(\begin{array}{cccccc} & y_5 & y_{10} & y_{20} & y_{21} & y_{23} \\ T_1 & 1 & 1 & 1 & 1 & 1 \\ T_2 & 1 & 0 & 0 & 0 & 0 \\ T_3 & 1 & 1 & 0 & 1 & 0 \\ T_4 & 1 & 0 & 0 & 0 & 0 \\ T_5 & 1 & 0 & 0 & 0 & 0 \\ T_6 & 1 & 0 & 0 & 0 & 0 \\ T_7 & 0 & 0 & 1 & 0 & 0 \\ T_8 & 0 & 1 & 1 & 1 & 1 \\ W & 1 & 1 & 1 & 1 & 1 \end{array}\right)$$

The proximity function between objects is $p_i(y_w, y_{T_i}), i = \overline{1,8};$ using P_{T_8}matrix:

$$P_{T_8}(W) = \left(\begin{array}{cccccc} & y_5 & y_{10} & y_{20} & y_{21} & y_{23} \\ T_1 & 1 & 1 & 1 & 1 & 1 \\ T_2 & 1 & 0 & 0 & 0 & 0 \\ T_3 & 1 & 1 & 0 & 1 & 0 \\ T_4 & 1 & 0 & 0 & 0 & 0 \\ T_5 & 1 & 0 & 0 & 0 & 0 \\ T_6 & 1 & 0 & 0 & 0 & 0 \\ T_7 & 0 & 0 & 1 & 0 & 0 \\ T_8 & 0 & 1 & 1 & 1 & 1 \end{array}\right)$$

When the$P_{T_8}(W)$ matrix is computed on a linear element, the value of the T_i (in our case T_8), which is relative to the unknown object W, is the sum of the differences in the parameters of the object of the diagnosis, ie the sum of the matrix elements: $\Gamma_w(P_{T_8}) = \Gamma_8(y_w, y_{T_1}) + \Gamma_8(y_w, y_{T_2}) + \cdots + \Gamma_8(y_w, y_{T_8}) = 5 + 1 + 3 + 1 + 1 + 1 + 1 + 4 = 17.$

The results obtained in the comparative assessment are presented in Table №5.

Table:5

	$\Gamma_w(P_{T_1})$	$\Gamma_w(P_{T_2})$	$\Gamma_w(P_{T_3})$	$\Gamma_w(P_{T_4})$	$\Gamma_w(P_{T_5})$	$\Gamma_w(P_{T_6})$	$\Gamma_w(P_{T_7})$	$\Gamma_w(P_{T_8})$
$\Gamma_{\overline{1,8};}(y_w, y_{T_1})$	13	4	4	2	1	2	5	5
$\Gamma_{\overline{1,8};}(y_w, y_{T_2})$	3	3	0	2	0	0	3	1
$\Gamma_{\overline{1,8};}(y_w, y_{T_3})$	4	1	3	1	0	0	3	3
$\Gamma_{\overline{1,8};}(y_w, y_{T_4})$	2	3	1	2	1	0	3	1
$\Gamma_{\overline{1,8};}(y_w, y_{T_5})$	2	2	1	2	3	1	5	1
$\Gamma_{\overline{1,8};}(y_w, y_{T_6})$	3	2	1	1	1	3	5	1
$\Gamma_{\overline{1,8};}(y_w, y_{T_7})$	3	2	1	1	2	2	6	1
$\Gamma_{\overline{1,8};}(y_w, y_{T_8})$	5	2	3	1	0	0	3	4

Step 10: From the values shown in Table №5, we create the following matrices:

$$S = \left(\begin{array}{ccccccccc} & \Gamma_w(P_{T_1}) & \Gamma_w(P_{T_2}) & \Gamma_w(P_{T_3}) & \Gamma_w(P_{T_4}) & \Gamma_w(P_{T_5}) & \Gamma_w(P_{T_6}) & \Gamma_w(P_{T_7}) & \Gamma_w(P_{T_8}) \\ \Gamma_{\overline{1,8};}(y_w, y_{T_1}) & 13 & 4 & 4 & 2 & 1 & 2 & 5 & 5 \\ \Gamma_{\overline{1,8};}(y_w, y_{T_2}) & 3 & 3 & 0 & 2 & 0 & 0 & 3 & 1 \\ \Gamma_{\overline{1,8};}(y_w, y_{T_3}) & 4 & 1 & 3 & 1 & 0 & 0 & 3 & 3 \\ \Gamma_{\overline{1,8};}(y_w, y_{T_4}) & 2 & 3 & 1 & 2 & 1 & 0 & 3 & 1 \\ \Gamma_{1,8;}(y_w, y_{T_5}) & 2 & 2 & 1 & 2 & 3 & 1 & 5 & 1 \\ \Gamma_{1,8;}(y_w, y_{T_6}) & 3 & 2 & 1 & 1 & 1 & 3 & 5 & 1 \\ \Gamma_{1,8;}(y_w, y_{T_7}) & 3 & 2 & 1 & 1 & 2 & 2 & 6 & 1 \\ \Gamma_{1,8;}(y_w, y_{T_8}) & 5 & 2 & 3 & 1 & 0 & 0 & 3 & 4 \end{array}\right)$$

Step 11: The values reflected in each of the columns of the generated S matrix are obtained in relation to the number of informative marks (Table №4) identified for the disease, ie the normalization of the obtained results, which results in the following matrixS^*.

$$S^* = \left(\begin{array}{ccccccccc} & \Gamma_w(P_{T_1}) & \Gamma_w(P_{T_2}) & \Gamma_w(P_{T_3}) & \Gamma_w(P_{T_4}) & \Gamma_w(P_{T_5}) & \Gamma_w(P_{T_6}) & \Gamma_w(P_{T_7}) & \Gamma_w(P_{T_8}) \\ \Gamma_{\overline{1,8};}(y_w, y_{T_1}) & 0,93 & 0,80 & 1,00 & 0,67 & 0,33 & 0,67 & 0,56 & 1,00 \\ \Gamma_{\overline{1,8};}(y_w, y_{T_2}) & 0,21 & 0,60 & 0,00 & 0,67 & 0,00 & 0,00 & 0,33 & 0,20 \\ \Gamma_{\overline{1,8};}(y_w, y_{T_3}) & 0,29 & 0,20 & 0,75 & 0,33 & 0,00 & 0,00 & 0,33 & 0,60 \\ \Gamma_{\overline{1,8};}(y_w, y_{T_4}) & 0,14 & 0,60 & 0,25 & 0,67 & 0,33 & 0,00 & 0,33 & 0,20 \\ \Gamma_{1,8;}(y_w, y_{T_5}) & 0,14 & 0,40 & 0,25 & 0,67 & 1,00 & 0,33 & 0,56 & 0,20 \\ \Gamma_{1,8;}(y_w, y_{T_6}) & 0,21 & 0,40 & 0,25 & 0,33 & 0,33 & 1,00 & 0,56 & 0,20 \\ \Gamma_{1,8;}(y_w, y_{T_7}) & 0,21 & 0,40 & 0,25 & 0,33 & 0,67 & 0,67 & 0,67 & 0,20 \\ \Gamma_{1,8;}(y_w, y_{T_8}) & 0,36 & 0,40 & 0,75 & 0,33 & 0,00 & 0,00 & 0,33 & 0,80 \end{array}\right)$$

Step 12: Calculate the values in the line elements of the generatedS^*matrix:

$$\Gamma_{S^*}(T_1) = 0{,}93 + 0{,}80 + 1{,}00 + 0{,}67 + 0{,}33 + 0{,}67 + 0{,}56 + 1{,}00 = 5{,}96;$$
$$\Gamma_{S^*}(T_2) = 0{,}21 + 0{,}60 + 0{,}00 + 0{,}67 + 0{,}00 + 0{,}00 + 0{,}33 + 0{,}20 = 2{,}01;$$
$$\Gamma_{S^*}(T_3) = 0{,}29 + 0{,}20 + 0{,}75 + 0{,}33 + 0{,}00 + 0{,}00 + 0{,}33 + 0{,}60 = 2{,}50;$$
$$\Gamma_{S^*}(T_4) = 0{,}14 + 0{,}60 + 0{,}25 + 0{,}67 + 0{,}33 + 0{,}00 + 0{,}33 + 0{,}20 = 2{,}52;$$

$\Gamma_{S^*}(T_5) = 0{,}14 + 0{,}40 + 0{,}25 + 0{,}67 + 1{,}00 + 0{,}33 + 0{,}56 + 0{,}20 = 3{,}55;$
$\Gamma_{S^*}(T_6) = 0{,}21 + 0{,}40 + 0{,}25 + 0{,}33 + 0{,}33 + 1{,}00 + 0{,}56 + 0{,}20 = 3{,}28;$
$\Gamma_{S^*}(T_7) = 0{,}21 + 0{,}40 + 0{,}25 + 0{,}33 + 0{,}67 + 0{,}67 + 0{,}67 + 0{,}20 = 3{,}40;$
$\Gamma_{S^*}(T_8) = 0{,}36 + 0{,}40 + 0{,}75 + 0{,}33 + 0{,}00 + 0{,}00 + 0{,}33 + 0{,}80 = 2{,}97.$

The obtained results (3) make the following inequality:

$\Gamma_{S^*}(T_1)>\Gamma_{S^*}(T_5)>\Gamma_{S^*}(T_7)>\Gamma_{S^*}(T_6)>\Gamma_{S^*}(T_8)>\Gamma_{S^*}(T_4)>\Gamma_{S^*}(T_3)>\Gamma_{S^*}(T_2)$.

Consequently, the given object W is higher than the object of the T_1- diagnostic object in relation to other objects of diagnostics.

III. Conclusion

The paper examines the issues of making medical diagnostic decisions on myocardial infarction diseases, which are the most common diseases of the cardiovascular system.

Due to the solution of the above tasks, the following results were achieved:

- to solve the first task, a complex of informativefeatures for diseases of theX_p-class was identifiedon the basis of a given training sample. The training sample is presented in the form of a table, when applyingtheT-matrixformed on its basis with respect to theTi–diagnostic object,the T_{T_i}-matrices are formed. Then, the function of inter-object remoteness$\theta_i(y_{Tk,}y_{Ti}), i = \overline{2,8};, j = \overline{1,23};, k = \overline{1,8};, j \neq k;$.is calculated, the comparative assessment of objects is carried out in the context of the elements of columns of theT_{T_1}, T_{T_2}, ... T_{T_8}-matrices.According to the results of the assessment, a complex of informative features was revealed in the context of objects of eachTi;

- using theT_{T_1}, T_{T_2}, ... T_{T_8}-matrices, calculated in the context of a complex of informative features according to the content of the second task, the issue of comparative evaluation of objects being diagnosed was solved. As a result of the assessment, the contribution of each diagnostic object Ti to the own class of theX_p objects is determined. Their value is$\Gamma(T_{T_1})$, $\Gamma(T_{T_2})$, ... $\Gamma(T_{T_8})$, and their average valueis calculated on the basis of$\overline{\Gamma}(T_{T_1})$, $\overline{\Gamma}(T_{T_2})$, ... $\overline{\Gamma}(T_{T_8})$;

- in accordance with the third task, a decisive rule, reflecting the belonging of an unknown object to a class when diagnosing, i.e. a sick person, was developed. The decision rule is constructed using the proximity function, the P-matrix is formed on the basis of the parameters of the unknown diagnostic object W and the comparative estimates of objects are calculated, and the$P_{T_1}(W)$, $P_{T_2}(W)$,... $P_{T_8}(W)$-matrices are created. Using this, an unknown object is evaluated in the context of inline elements in the following form$\Gamma_w(P_{T_1})$, $\Gamma_w(P_{T_2})$,... $\Gamma_w(P_{T_8})$.

On the basis of the obtained results, the S-matrixandthe normalizedS^*andthe estimates of the unknown object$\Gamma_{S^*}(T_1)$, $\Gamma_{S^*}(T_2)$,... $\Gamma_{S^*}(T_8)$ are calculated with respect to the diagnostic objects and in accordance with the formula (6), thefollowing inequality is created:

$\Gamma_{S^*}(T_1)>\Gamma_{S^*}(T_5)>\Gamma_{S^*}(T_7)>\Gamma_{S^*}(T_6)>\Gamma_{S^*}(T_8)>\Gamma_{S^*}(T_4)>\Gamma_{S^*}(T_3)>\Gamma_{S^*}(T_2)$.

On this basis, a high level of belonging of the given unknown object W to the T_1.-diagnostic object relative to other objects was revealed.

Thus, the classification of medical image recognition is described in a sequence of tasks based on algorithms for calculating estimates, and software was developed in an object-oriented Java programming language using the theoretical results obtained. The developed software was investigated within the framework of applied tasks of diagnostic decision making processes.

IV. References

[1]. Zhuravlev Yu.I. Selected scientific works. –M: 'Magistr' Publishing house, 1998. - 420 p.
[2]. Zagoruiko N.G. Applied methods of data and knowledge analysis. Novosibirsk: Publishing House of the Inst. of Mathematics, 1999. - 270 p.
[3]. Zhuravlev Yu.I., Ryazanov V.V., Senko O.V. Recognition. Mathematical methods. Software system Practical applications. M.: Fazis, 2006. – 159 p.
[4]. Khaykin S. Neural Networks: The Complete Book. M .: Williams. 2006. - 1104 p.
[5]. Kamilov M.M., Mirzaev N.M., Radjabov S.S. On one modification of the model of recognition algorithms based on the estimation // Reports of the Academy of Sciences of the Republic of Uzbekistan. Tashkent, 2009. No. 2. - pp.18-20.
[6]. Kamilov M.M., Mirzaev N.M., Radjabov S.S. The current state of the issues of constructing models of recognition algorithms // Chemical Technology. Control and Management. Tashkent. 2009. No. 2. - pp.67-72.
[7]. Vorontsov K.V. Combinatorial theory of learning reliability for precedents. Dis. for the degree of Ph.D. Med. Sc. M.: CC of RAS, 2010. - 232 p.
[8]. Sh.Kh. Fazylov, N.M. Mirzaev, S.S. Radjabov Constructing a model of algorithms for calculating estimates taking into account the high dimensionality of the feature space. Bulletin of GGTU, 2012, No.1 (64), Issue 2. - 274-279 pp.
[9]. Nefedov A.V. Effective algorithms based on the calculation of estimates, with rectangular reference sets for image recognition problems. Dis. for the degrees Ph.D. Med. Sc.: CC of RAS, 2012. - 124 p.
[10]. Kamilov M.M., Nishanov A.Kh., Beglerbekov R.Zh. The use of decision rules for the selection of informative feature sets // Chemical technology.

Control and Management. - Tashkent, 2017, No.3. - 82-85.

[11]. Kamilov M.M., Nishanov A.Kh., Djuraev G.P. Algorithm for classification of medical data in the space of informative features using the function of distance and proximity//Chemical Technology. Control and Management. - Tashkent, 2018, No. 1-2. –pp. 143-150.

[12]. Nishanov A.Kh., Djuraev G.P., Narziyev N.B. The use of algorithms for calculating estimates in myocardial infarction diseases/ Descendants of Muhammad al-Khwarizmi. - Tashkent, 2018, No. 2. - 40-44 pp.

[13]. Fazylov Sh.Kh., Nishanov A.Kh., Mamatov N.S. Methods and algorithms for selection of informative features based on heuristic criteria of informativeness. Tashkent: Fan va Tekhnologiya. 2017 - 132 p.