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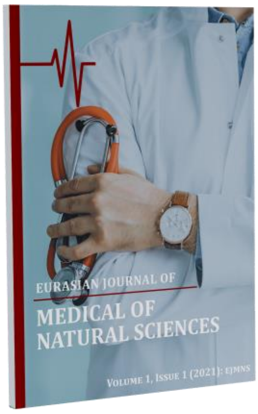

MODELING CARDIOVASCULAR RISK AND RISK FACTORS IN PATIENTS WITH CARDIOVASCULAR DISEASES

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ABSTRACT

Cardiovascular diseases (CVDs) remain a pressing issue in most countries worldwide. Initially, cardiovascular and then other chronic non-communicable diseases became the leading cause of mortality in economically developed countries [2]. However, sufficient scientific knowledge has been accumulated to confirm the presence of factors that contribute to the development and progression of these diseases, known as risk factors (RFs) [5]. The contemporary evidence-based strategy for CVD prevention is the concept of risk factor stratification.

Introduction

The developed model aims to identify risk factors for cardiovascular diseases (CVDs), assess the overall cardiovascular risk level, and determine the risk groups based on the likelihood of developing CVDs in a population with a very high risk at the primary healthcare level [1]. The model utilizes the findings of several epidemiological studies that indicate the association between risk factors and the occurrence of fatal and non-fatal coronary and other cardiovascular events (such as the Framingham and SCORE studies). The implementation of preventive measures not only contributes to reducing the incidence and mortality of CVDs but also facilitates early identification of risk factors and the implementation of preventive measures [3,4].

One of the significant achievements in cardiovascular epidemiology is the transition from assessing individual risk factors to evaluating the overall, or cumulative, risk, in other words, the development of prognostic models. The results obtained from the Framingham study enabled the development of a methodology for multidimensional modeling of the risk of developing CVDs and their complications. In 1976, the first system for predicting the cumulative risk of developing coronary heart disease (CHD) was created using logistic regression [5].

In 2003, the European Society of Cardiology and other expert groups introduced the SCORE (Systematic Coronary Risk Evaluation) scale, which was developed based on the results of European studies. The scale provided variants for countries with low and high mortality rates from CVDs [7,8]. However, it was noted that the assessment of cumulative risk using the SCORE database could and should be adapted based on national conditions, resources, and priorities, as it considers the heterogeneity of cardiovascular diseases and mortality in different European populations. The SCORE scale should be considered as a foundation upon which all necessary adaptive changes can be made to account for local socio-economic conditions and healthcare system conditions. Recently, the results of comparing the Framingham Risk Score (FRS) and the European SCORE scale were published [5,7]. The authors presented data on the use of FRS and SCORE in predicting coronary complications in British men aged 40-59 years based on social status and showed that both scales yielded an excess risk in all social strata.

The distinctive feature of this model is that the risk is expressed by calculating the absolute probability of developing a fatal cardiovascular complication in the next 10 years. Patients diagnosed with CVD and individuals at high risk of developing these diseases are the priority clinical groups for healthcare professionals.

The main risk factors that contribute to the cumulative risk and affect the prognosis can be identified through relatively simple screening using standard methods. Based on the results of initial screening, risk groups can be identified based on the level of absolute risk (using the multidimensional model) and the level of relative risk (in comparison to a typical representative of the population or any other reference group) [1,6].

The SCORE scale is also one of the most successful examples of automated risk assessment systems as it exists in electronic form on websites and is distributed in the form of discs for installation on desktop computers [2].

Scientists in Samara have developed an automated system for non-invasive monitoring of the risk level of developing cardiovascular diseases (CVDs) and their complications [2]. In this automated system, patient data such as systolic, diastolic, and pulse blood pressure are used to assess the degree of risk. It takes into account the heart rate, presence of arrhythmia, evaluates the pulse wave velocity, and calculates indicators of blood viscosity and hematocrit. The assessment of the risk level of developing CVDs and their complications is conducted using the original "Pulse" program version 2.0. The automated system allows for non-invasive prediction of the risk of developing atherosclerosis and hypertension within 2-3 minutes. It can detect early, preclinical stages of atherosclerosis (endothelial dysfunction) and monitor the clinical course of the atherosclerotic process.

Objective of the study: To conduct a multifactor analysis of indicators reflecting cardiovascular risk and identify prognostically unfavorable factors of increased cardiovascular risk (CVR) in the population, and to create a predictive model for cardiovascular risk in patients with cardiovascular diseases (CVDs) who were previously not diagnosed with CVDs.

Materials and methods: A total of 250 individuals aged 40-70 without verified CVDs were examined, including 80 males. The planned clinical, laboratory, and instrumental examination included a standard questionnaire designed to assess the objective condition of the patients. It involved the evaluation of hemodynamic and anthropometric indicators such as body weight, height, waist and hip circumference, blood pressure (BP), body mass index (BMI), electrocardiogram (ECG), biochemical analysis of lipid profile (cholesterol, low-density lipoprotein, triglycerides, high-density lipoprotein, atherogenic index), serum glucose, creatinine, urea, serum uric acid level, C-reactive protein. The glomerular filtration rate (GFR) was calculated using the CKD-EPI formula. Vascular elasticity and biological age were determined using plethysmography. A 10-year risk of death and fatal cardiovascular events (myocardial infarction, stroke) in practically healthy individuals were assessed using the SCORE-2 questionnaire. The composition of body mass was evaluated using bioimpedance analysis on the Tanita device. The quality of life (QoL) and stress index were assessed using the Reeder L. questionnaire and the EQ-5D health and QoL assessment questionnaire, EQ-VAS scale, and patients' physical fitness (PF) were evaluated. Exercise tolerance indicators were also assessed, including the 6-minute walk test, Borg scale for dyspnea intensity, Rufier test, and the mass test for determining physical condition according to E.A. Pirogov, 1984. Unfavorable factors of increased cardiovascular risk were evaluated. To determine the most significant indicators for assessing cardiovascular health and CVR, a method of calculating feature contributions in the decision-making process was used, based on the theory of pattern recognition with a probabilistic approach.

2. Methods and models

Based on the results of the clinical procedure, we determine the severity of ischemic heart disease in the following stages (in ascending order):

d_1 -Neurocirculatory dystonia syndrome

d_2 - Moderate degree of neurocirculatory dystonia

d_3 - Severe degree of neurocirculatory dystonia

d_4 - Primary functional angina (stable angina)

d_5 - Secondary functional angina

d_6 - Tertiary functional angina

When determining the stages required to identify the phases, we take into account the following $d_1 - d_6$ key parameters measured in laboratory conditions for establishing the diagnosis of ischemic heart disease in relation to a specific patient (with changes within the normal range for each age):

x_1 -Patient's age (31-57 years)

x_2 -Double increase in pulse pressure (147-405)

x_3 -Physical exercise tolerance (90-1200 kgm/min)

x_4 -Ratio of patient's weight change per 1 kg to double increase in pulse pressure (0.6-3.9)

x_5 -Ratio of pulse pressure change to 1 kg of load (0.1-0.4)

x_6 -Adenosine triphosphate (ATP) levels (34.5-66.2 mmol/l)

x_7 -Adenosine diphosphate (ADP) levels (11.9-29.2 mmol/l)

x_8 -Adenosine monophosphate (AMP) levels (3.6-27.1 mmol/l)

x_9 -Phosphorylation coefficient (1-5.7)

x_{10} - maximum oxygen consumption by a patient relative to 1 kilogram of their weight ranges from 10.5 to 40.9 milliliters per minute per kilogram.

x_{11} - The ratio of the change in cardiac index in response to submaximal load ranges from 46 to 312.

x_{12} - the ratio of the coefficient of composition between dry and fatty acids ranges from 3.9 to 22.8. The measured parameters (excluding age) are evaluated together in their entirety when diagnosing, under laboratory conditions. $d_j \ (j = \overline{1,6})$ implies the selection of one of the options.

Parameters $x_1 \div x_{12}$, ones mentioned above will be considered as linguistic variables. Additionally, we will introduce the following linguistic variables:

d - The danger of ischemic heart disease, which is measured by levels of $d_1 \div d_6$; y - andнструментальная опасность, которая завandcandт от параметров $\{x_2, x_3, x_4, x_5, x_{10}, x_{11}\}$; z - Instrumental danger, which depends on parameters $\{x_6, x_7, x_8, x_9, x_{12}\}$.

structure of the model for the differential diagnosis of ischemic heart disease in the form of a logical inference tree that corresponds to the relationships:

$$d = f_d\left(x_1, y, z\right), \qquad (8.1)$$

$$y = f_y\left(x_2, x_3, x_4, x_5, x_{10}, x_{11}\right), \qquad (8.2)$$

$$z = f_z\left(x_6, x_7, x_8, x_9, x_{12}\right).$$

Fuzzy logical diagnostic model of ischemic heart disease.

If (x_1=H and y=H and z=H)

or (x_1=H and y=HC and z=HC) (8.3)

or (x_1=HC and y=HC and z=H)

then d= d_1

If (x_1=HC and y=HC and z=HC)

or (x_1 =C and y=HC and z=HC)

or (x_1 =HC and y=HC and z=C)

then d= d_2

If (x_1 =C and y=HC and z=C)

or (x_1 =BC and y=BC and z=HC)

or (x_1 =BC and y=C and z=C)

then d= d_3

If (x_1 =BC and y=C and z=BC)

or (x_1 =C and y=BC and z=BC)

or (x_1 =BC and y=BC and z=BC)

then d= d_4

If (x_1 =C and y=B and z=C)

or (x_1 =BC and y=BC and z=B)

or (x_1 =B and y=BC and z=BC)

then d= d_5

If (x_1 =B and y=B and z=B)

or (x_1 =BC and y=B and z=BC)

or (x_1 =C and y=B and z=BC)

then d= d_6

Here:

If (x_2 =B and x_3 =B and x_4 =B and x_5 =H and x_{10} =B and x_{11} =B)

or (x_2 =B and x_3 =BC and x_4 =B and x_5 =HC and x_{10} =B and x_{11} =B)

or (x_2 =BC and x_3 =B and x_4 =BC and x_5 =H and x_{10} =B and x_{11} =B)

then y=H

If (x_2 =BC and x_3 =BC and x_4 =B and x_5 =HC and x_{10} =B and x_{11} =BC)

or (x_2 =B and x_3 =B and x_4 =BC and x_5 =C and x_{10} =B and x_{11} =B)

or (x_2 =BC and x_3 =B and x_4 =BC and x_5 =H and x_{10} =BC and x_{11} =BC)
then y=HC

If (x_2 =C and x_3 =C and x_4 =C and x_5 =C and x_{10} =C and x_{11} =C)

or (x_2 =BC and x_3 =BC and x_4 =C and x_5 =HC and x_{10} =BC and x_{11} =C)

or (x_2 =C and x_3 =BC and x_4 =BC and x_5 =C and x_{10} =BC and x_{11} =BC)
then y=C

If (x_2 =HC and x_3 =C and x_4 =HC and x_5 =BC and x_{10} =HC and x_{11} =HC)

or (x_2 =HC and x_3 =HC and x_4 =C and x_5 =C and x_{10} =H and x_{11} =HC)

or (x_2 =C and x_3 =HC and x_4 =HC and x_5 =BC and x_{10} =HC and x_{11} =C)
then y=BC

If (x_2 =H and x_3 =H and x_4 =H and x_5 =BC and x_{10} =H and x_{11} =H)

or (x_2 =HC and x_3 =H and x_4 =HC and x_5 =B and x_{10} =H and x_{11} =HC)

or (x_2 =H and x_3 =HC and x_4 =HC and x_5 =BC and x_{10} =H and x_{11} =H)
then y=B

If (x_6 =B and x_7 =B and x_8 =B and x_9 =B and x_{12} =B)

or (x_6 =BC and x_7 =B and x_8 =BC and x_9 =BC and x_{12} =BC)

or (x_6 =B and x_7 =BC and x_8 =B and x_9 =C and x_{12} =BC)
then z=H

If (x_6 =BC and x_7 =BC and x_8 =C and x_9 =C and x_{12} =BC)

or (x_6 =C and x_7 =BC and x_8 =C and x_9 =BC and x_{12} =C)

or (x_6 =C and x_7 =B and x_8 =BC and x_9 =BC and x_{12} =BC)
then z=HC

If (x_6 =C and x_7 =C and x_8 =C and x_9 =BC and x_{12} =BC)

or (x_6 =BC and x_7 =BC and x_8 =C and x_9 =C and x_{12} =C)

or (x_6 =BC and x_7 =C and x_8 =BC and x_9 =BC and x_{12} =C)
then z=C

If (x_6 =HC and x_7 =C and x_8 =HC and x_9 =C and x_{12} =C)
or (x_6 =BC and x_7 =HC and x_8 =C and x_9 =HC and x_{12} =HC)
or (x_6 =H and x_7 =C and x_8 =C and x_9 =HC and x_{12} =C)
then z=BC

If (x_6 =H and x_7 =H and x_8 =H and x_9 =H and x_{12} =HC)
or (x_6 =HC and x_7 =H and x_8 =HC and x_9 =H and x_{12} =H)
or (x_6 =H and x_7 =HC and x_8 =HC and x_9 =H and x_{12} =HC)
then z=B

To evaluate the values of linguistic variables $x_1 \div x_{12}$, and also y and z, We will use a unified scale of qualitative terms: L - low, LM - lower medium, M - medium, UM - upper medium, H - high. Each of these terms represents a fuzzy set defined by its corresponding membership function.

In the general case, each input variable $x_1 \div x_{12}$ have their own membership functions for fuzzy terms (L, LM, M, UM, H) that are used in equations. To simplify the modeling, we will use the same membership functions for all variables $x_1 \div x_{12}$ We will use only one form of membership functions. To achieve this, we will normalize the ranges of each variable to a common universal interval $[0,4]$ Using the following relationships:

$$\mu^j(x_i) = \tilde{\mu}^j(u), \quad u = 4\frac{x_i - \underline{x}_i}{\overline{x}_i - \underline{x}_i}, \quad j = H, нC, C, вC, B,$$

where $[\underline{x}_i, \overline{x}_i]$ - range of variation of the variable x_i, $i = \overline{1,12}$.
The range of variation of the variable

$$\tilde{\mu}^j(u) = \frac{1}{1 + \left(\frac{u-b}{c}\right)^2}, \qquad (8.7)$$

3. Result
The decision-making algorithm
1. The algorithm begins by determining the training sample:

$$\begin{vmatrix} x_1^1 & x_2^1 & \dots x_n^1 \\ x_1^2 & x_2^2 & \dots x_n^2 \\ . & . & . \\ x_1^m & x_2^m & \dots x_n^m \end{vmatrix} \quad \begin{vmatrix} y_1 \\ y_2 \\ \dots \\ y_m \end{vmatrix}.$$

2. In the next step, the normalization of the study sample is carried out:

$$u_i^k = l\frac{x_i^k - x^{\min}}{x^{\max} - x^{\min}};$$

here $i = \overline{1,n},\ k = \overline{1,m}.$

The fuzzification operation has been performed:

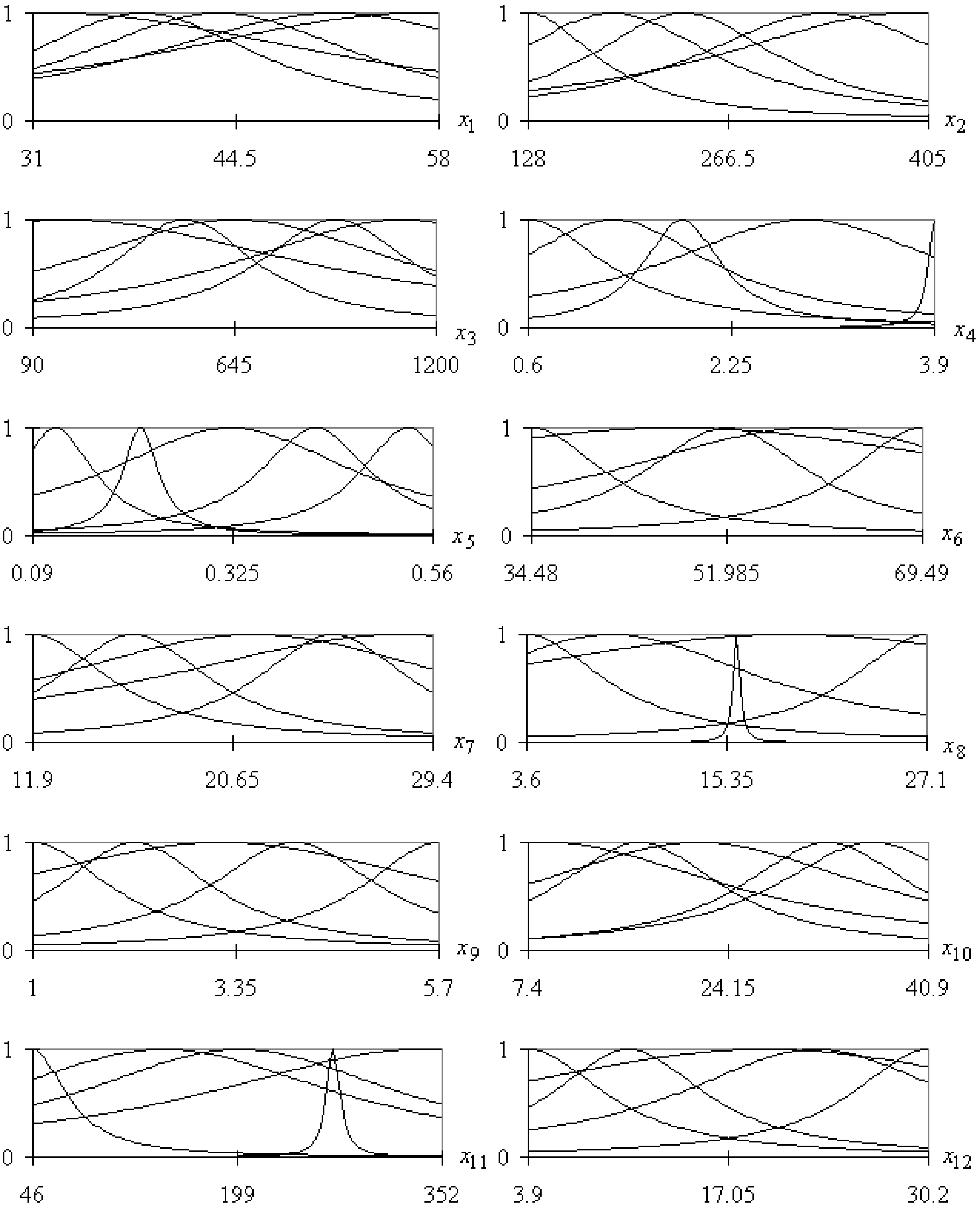
$$\mu^j\left(u_i^k\right) = \frac{1}{1 + \dfrac{u_i^k - b_j}{c_j}};$$

here c_j, b_j -parameters, $j = \overline{1,l}.$ l – number that determine the interval.

4. Let's fix the values of the patient's state parameters

$$X^* = \left(x_1^*, x_2^*, \dots x_{12}^*\right).$$

5. Using the model and parameters b and c, let's determine the values of the membership functions. $\mu^j\left(x_i^*\right)$, at fixed parameter values x_i^*, $i = \overline{1,12}$.



Graphs of Membership Functions 6.

Using logical equations, we will calculate the values of the membership functions

$\mu^{d_j}\left(x_1^*, x_2^*, \ldots, x_{12}^*\right)$ for a state vector $X^* = \left(x_1^*, x_2^*, \ldots, x_{12}^*\right)$ for all diagnoses $d_1, d_2, \ldots, d_6$. In this case, logical AND ($\wedge$) and OR($\vee$) operations are performed on the membership functions, replacing the operations with min and max:

$$\mu(a) \wedge \mu(b) = min[\mu(a), \mu(b)],$$

$$\mu(a) \vee \mu(b) = max[\mu(a), \mu(b)].$$

7. Let's determine the solution d_j^*, for which:

$$\mu^{d_j^*}\left(x_1^*, x_2^*, \ldots, x_{12}^*\right) = \max_{j=1,12}\left[\mu^{d_j}\left(x_1^*, x_2^*, \ldots, x_{12}^*\right)\right].$$

Table 1.
Development and verification of diagnostic models.

	Diagnosis	
No	Doctor's diagnosis	Computer diagnosis
1	d1	d1
2	d1	d1
3	d2	d2
4	d2	d2
5	d3	d3
6	d3	d3
7	d4	d4
8	d4	d4
9	d5	d5
10	d5	d6 *
11	d6	d6
12	d6	d6
13	d1	d2 *
14	d1	d1
15	d2	d4 **
16	d2	d2
17	d3	d3
18	d3	d4 *
19	d4	d4
20	d4	d4
21	d5	d5
22	d5	d5

23	d6	d6
24	d6	d6
25	d1	d1
26	d1	d1
27	d1	d1
28	d1	d2 *
29	d1	d1
30	d1	d1
31	d1	d1
32	d2	d2
33	d2	d2
34	d2	d2
35	d2	d2
36	d2	d2
37	d2	d2
38	d2	d2
39	d3	d3
40	d3	d3
41	d3	d3
42	d3	d4 *
43	d3	d3
44	d3	d3
45	d3	d3
46	d4	d4
47	d4	d4
48	d4	d4
49	d4	d4
50	d4	d4
51	d4	d4
52	d4	d4
53	d5	d5
54	d5	d5
55	d5	d5
56	d5	d5
57	d4	d5*
58	d5	d5
59	d5	d5
60	d6	d6
61	d6	d6
62	d6	d6
63	d6	d6

64	d6	d6
65	d6	d6

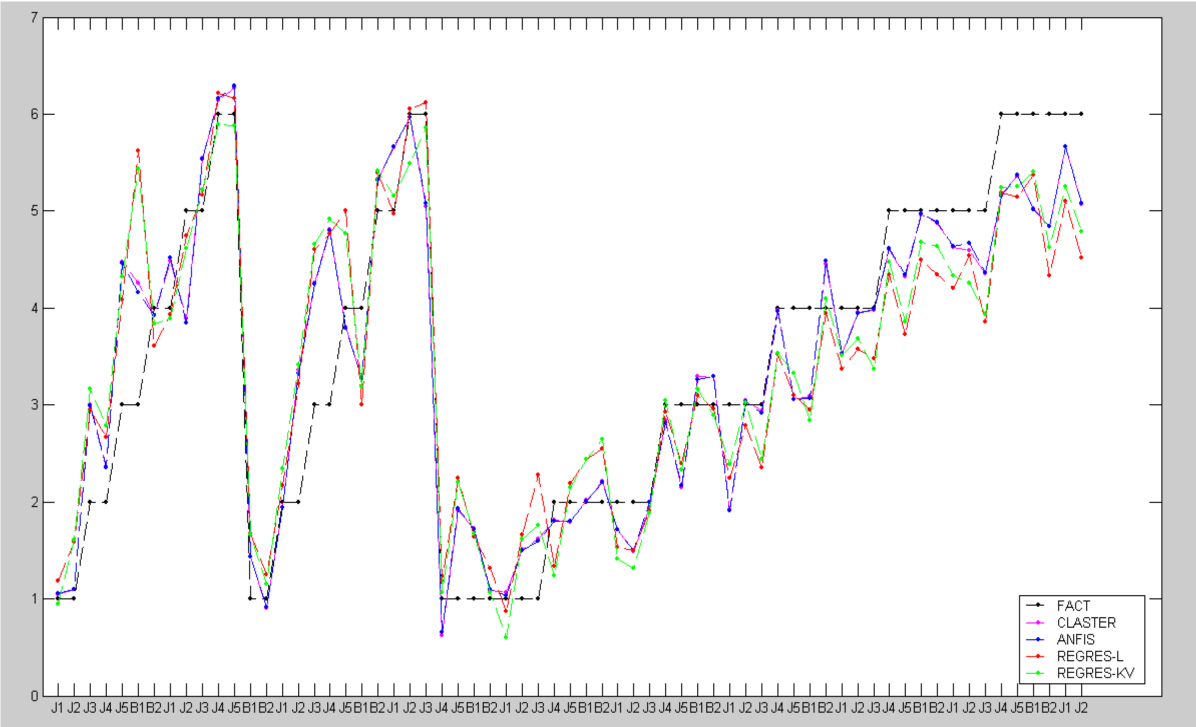


Table 1. Comparison of Diagnoses by the Doctor and the Computer

4. Conclusion

When solving complex diagnostic tasks, we use simplified structures of expert systems based on experience to reduce the time required for developing and verifying mathematical models and analyzing mathematical tools. We also establish communication with the system creator to obtain necessary data and feedback.

1. In simplified expert systems, absolute certainty in the decisions made is not required. The system provides a level of confidence in the decision, allowing the user to critically evaluate the response.
2. Simplified expert systems allow for modeling decision-making situations.
3. Simplified expert systems provide very fast responses (fraction of a second), enabling their use in decision-making processes that require high speed in various dynamic systems.

The capabilities of simplified networks (such as adjusting classification models, minimizing training parameters, etc.) simplify the process of creating expert systems and determine the direction of scientific research. The effectiveness of simplified expert systems is primarily evaluated through practical results, involving multiple experiments and verifications under different conditions.

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