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# APPLICATION OF MATHEMATICAL MODELS IN THE DIAGNOSIS OF DISEASES OF INTERNAL ORGANS

**Abstract**:The application of diagnostic expert systems in medical technology signifies a notable progression, as they provide a computerized framework for decision-support, assisting healthcare practitioners in the process of disease diagnosis. These systems facilitate the integration of patient data, encompassing symptoms and medical history, with a knowledge base in order to produce a comprehensive compilation of potential diagnoses. Through the utilization of knowledge-based methodologies, they enhance these potentialities in order to ascertain the most probable diagnosis. The present study examines expert systems, investigating their historical development, architectural structure, and the approaches utilized for knowledge representation. There is a significant emphasis placed on the advancement and implementation of these systems within the medical industry of Kazakhstan. This paper provides a comprehensive analysis of the benefits and drawbacks associated with diagnostic expert systems, emphasizing their potential to bring about significant advancements in medical fields. The study places significant emphasis on the necessity of developing and conducting thorough testing of these systems in order to improve the precision and effectiveness of medical diagnostics. The statement recognizes the importance of continuous research in order to enhance the design and implementation of these systems in various healthcare settings. This research makes a notable addition by examining optimization theory in the field of medical diagnosis. This study presents novel approaches for effectively addressing the intricacies and uncertainties associated with the diagnosis of complicated disorders. The work presents methodology for navigating the complex field of medical diagnostics by utilizing mathematical modeling and optimization approaches, specifically the gradient projection method. The utilization of diverse ways to tackle qualitative ambiguities in this approach signifies a significant progression inside the domain of diagnostic expert systems.

**Keywords**: Diagnosing diseases with the automated system; medical diagnostic expert systems; decision support systems; mathematical modelling.

**Introduction**

Diagnostic systems are computer-based decision-support systems that are designed to aid healthcare practitioners in disease diagnosis. Their purpose is to generate a list of potential diagnoses by analyzing a patient's symptoms, medical history, and other pertinent data.

A diagnostic information system operates by collecting information from a patient, including symptoms and medical history, to provide a list of possible diagnoses. The system utilizes knowledge-based methodologies, such as decision trees and rule-based systems, to narrow down the list of potential diagnoses to arrive at a final diagnosis.

This research paper provides an overview of expert systems, including their history, architecture, knowledge representation. It also discusses the advantages and limitations of expert systems, as well as their applications in different fields. There have been numerous research studies in the field of systems for diagnosing diseases, particularly in the area of medical expert systems and decision support systems. The article presents mathematical techniques for identifying serious medical problems such as myocardial infarction, shock (third degree), perforated peritonitis, and acute circulatory failure. The methods are based on optimization theory, a mathematical area that aims to discover the optimal answer among a range of possible alternatives. These models provide a systematic and effective strategy for detecting complicated diseases by utilizing techniques like the gradient projection method and methods tailored to address qualitative ambiguity. The paper thoroughly analyzes the advantages and drawbacks of information systems in medicine, offering an impartial perspective essential for future advancements in this field. The study explores the uses of expert systems in several domains, emphasizing their significance in healthcare and promoting multidisciplinary collaboration and innovation.

This research study contributes significantly to the field of diagnostic expert systems by incorporating mathematical optimization approaches into the diagnostic process, providing a unique and methodical method for finding intricate disorders. This integration improves diagnostic expert systems and establishes a basis for future research to develop more precise and effective diagnostic tools.

**Research contribution** of this study makes a substantial contribution to the domain of medical diagnostics and expert systems by its investigation and exhibit of the adaptability and efficacy of various diagnostic table kinds and procedures in the context of disease diagnosis. This study providesthe different kinds of diagnostic table formats, demonstrating the optimal utilization of many types of input in the diagnostic process. These inputs include qualitative ambiguous information (e.g., "rare," "typical," "often"), weighted symptoms, and binary representation (0 and 1). The presence of diverse diagnostic inputs highlights the versatility and inclusiveness of expert systems in effectively managing a wide range of data types to assist in medical diagnosis.The research showcases the adaptability and resilience of expert systems in understanding and processing diverse information by utilizing various techniques to analyze these diagnostic tables.

**The purpose of the article** is to develop mathematical approaches to the effective diagnosis of diseases of internal organs when creating automated diagnostic systems. One study published in the Journal of Medical Internet Research evaluated the effectiveness of a mobile application-based decision support system for the diagnosis and treatment of common child-

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hood illnesses in a low-resource setting [1]. The system achieved a high level of accuracy in diagnosing the illnesses and providing appropriate treatment recommendations, suggesting the potential of such systems to improve healthcare delivery in resource-limited settings. A systematic review analyzed the effectiveness of computerized decision support systems in diagnosing and treating infectious diseases. The review found that such systems were effective in improving the accuracy and efficiency of diagnosis and treatment of infectious diseases, highlighting their potential for improving healthcare outcomes [1]. Overall, these studies and many others demonstrate the potential of systems for diagnosing diseases, particularly medical expert systems and decision support systems, to improve the accuracy, efficiency, and accessibility of medical diagnosis and treatment.

As demonstrated in our prior research [2], the format of medical databases varies. Diagnostic tables for a specific group of disorders specify the weight of symptoms using either numerical values or linguistic factors like “often” or “rarely.” The significance of the proposed research is in demonstrating the potential to utilize diagnostic tables that categorize symptom scales for certain diseases into two types: 1 for “symptom present” and 0 for “no symptom”[3].

This method is utilized in healthcare for the initial assessment of patients. This study demonstrates the feasibility of developing a mathematical diagnostic model within a single database representation. Furthermore, the model considers the severity of symptoms, highlighting the distinctiveness of this study. Its application in healthcare is expected to provide specific advantages in disease diagnosis.

*Diagnosing a disease* is the process of finding out what is causing someone’s medical symptoms. It’s like solving a puzzle, where the doctor has to gather information and put the pieces together to make a complete picture [3].There are several ways doctors can diagnose a disease [3], including:

- Physical examination: The doctor will check your body for any signs of the disease, such as rashes, lumps, or swelling.
- Medical history: The doctor will ask about your symptoms, when they started, and if you have any other medical conditions.
- Laboratory tests: The doctor may take samples of blood, urine, or other bodily fluids to be tested in a lab for any signs of the disease.
- Imaging tests: The doctor may use X-rays, CT scans, or MRI scans to see inside your body and look for any abnormal structures or conditions.

Once all of this information has been gathered, the doctor will use it to make a diagnosis and recommend the best treatment plan. It’s important to remember that getting a proper diagnosis is a crucial step in treating a disease, so it’s important to be open and honest with your doctor about your symptoms and medical history [4].

**Literature review for medical expert systems**

Medical expert systems have been created to aid healthcare workers in making well-informed judgments and enhancing the precision of diagnosis.Research indicates that medical expert systems are efficient in diagnosing a range of ailments, such as cardiovascular disease, infectious diseases, and malignancies. These technologies have been shown to enhance diagnostic accuracy, optimize clinical decision-making, and shorten the time to diagnosis [5]. However, there are limitations, like the requirement for frequent updates to the knowledge base to keep up with advancements in medical knowledge, the risk of biased decision-making if the knowledge base lacks diversity and representation, and the necessity for thorough validation and verification of the system to guarantee its accuracy.

The refore, medical automated diagnosing systems have the potential to enhance the precision and effectiveness of illness diagnosis, but they also pose obstacles that need to be resolved to maximize their benefits.  Automated systems have been established to aid in disease diagnosis since the late 1970s.

Various medical expert systems have been created to assist healthcare workers in diagnosing and treating diseases. Expert systems have been most commonly used for medical diagnosis.An expert system can aid a clinician in identifying a patient's medical issues or interpreting medical test findings [6].

"Isabel" is an online diagnostic expert system that offers information on more than 6,000 medical disorders. It is created to aid healthcare professionals in diagnosing intricate medical disorders, such as rare and uncommon ones. This tool is a clinical decision support system designed to assist doctors in creating a list of potential diagnoses by analyzing patient symptoms and other clinical data. The system utilizes a knowledge-based method to create a prioritized list of potential diagnoses and offers further details on each illness [7].

The Inferelator is a medical diagnostic expert system that employs machine learning algorithms to aid healthcare professionals in diagnosing complex medical conditions [8]. The system is created to amalgamate data from many sources such as medical records, lab findings, and imaging studies in order to produce a compilation of potential diagnoses. The Inferelator is a computational tool that uses machine learning methods to detect gene regulatory networks from high-throughput genomic data. It aids researchers in pinpointing the genes and pathways associated with different biological processes.Figure 1 illustrates is a brief chronology of research in expert systems for diagnosing diseases:

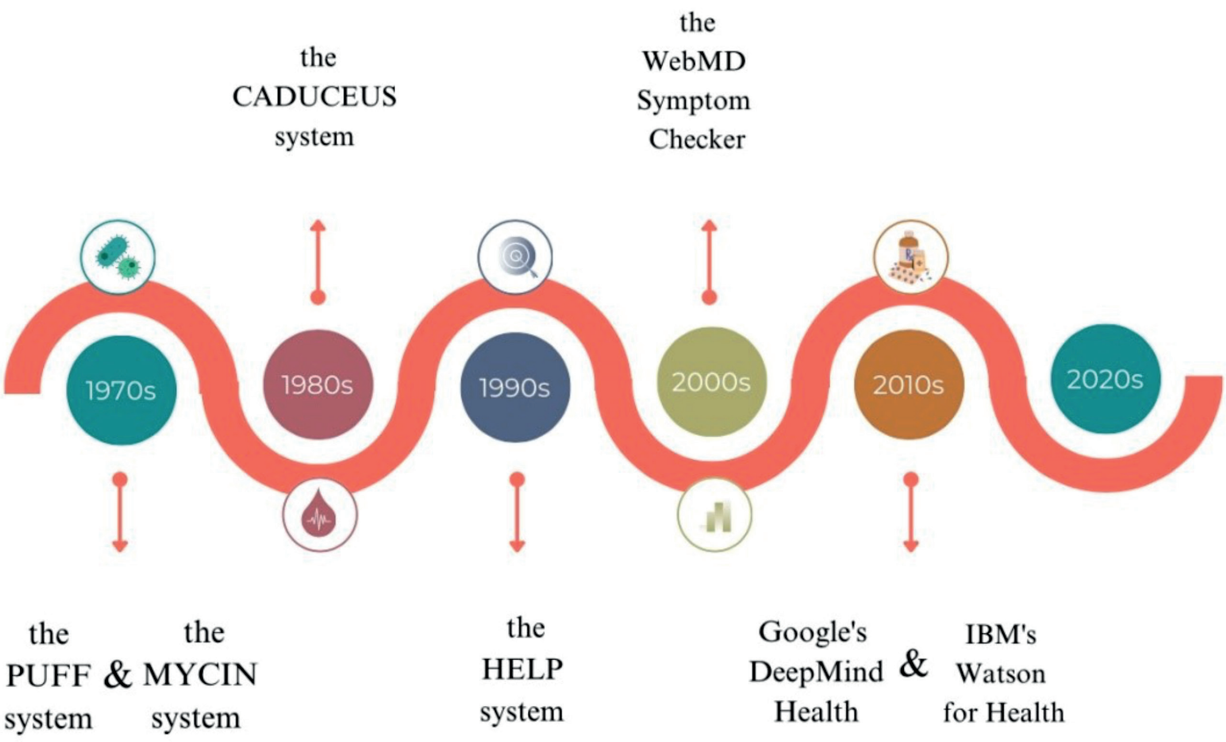


Figure 1. A brief chronology of research in systems for diagnosing

Global Infectious Diseases and Epidemiology Network is a web-based diagnostic expert system that provides information on infectious diseases and their diagnosis [9]. The system can offer details regarding diagnostic testing and treatment choices. This resource compiles data on more than 2,000 infectious diseases, covering details such as epidemiology, diagnosis, treatment, and prevention.

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IBM's Watson for Health is an artificial intelligence-powered system designed to assist healthcare professionals in making clinical decisions. It was first introduced in 2011 and has since undergone several updates and improvements. Watson for Health uses natural language processing, machine learning, and other advanced technologies to analyze vast amounts of medical data, including electronic health records, medical journals, and clinical trials [10]. System can analyze a patient's medical history and symptoms to suggest a list of possible diagnoses, along with the likelihood of each diagnosis. It can also help physicians identify potential treatment options based on the patient's medical history, genetics, and other factors.

Google's DeepMind Healthis a research-based division of Google's artificial intelligence company, DeepMind. It was established in 2016 to apply machine learning and other advanced technologies to healthcare research and development [11]. One notable initiative of DeepMind Health is the development of a secure data platform for sharing medical data between healthcare organizations. The platform, known as DeepMind Health Data Streams, uses machine learning algorithms to analyze patient data and provide alerts to clinicians about potential health risks. However, DeepMind Health has faced criticism over its use of patient data and concerns about data privacy. In response, the company has established a number of policies and procedures to ensure the responsible use of patient data and the protection of patient privacy [11].

Moreover, to assisting healthcare professionals, Watson for Health can also help patients better understands their health and treatment options. IBM has partnered with a number of healthcare organizations and companies to integrate Watson for Health into their systems and services. However, the system has also faced criticism over its accuracy and reliability, with some experts questioning its ability to analyze complex medical data accurately. IBM has continued to improve and refine Watson for Health, and it remains a significant development in the field of healthcare technology [12].

**Situation in Kazakhstan**

Healthcare practitioners in Kazakhstan utilize a range of instruments and methods to diagnose diseases, such as physical examinations, laboratory tests, scans, and medical history evaluations. Medical diagnostic automated systems are being more widely used in Kazakhstan as healthcare practitioners aim to enhance the precision and effectiveness of diagnosis. Diagnostic automated systems can assist healthcare providers by consolidating data from several sources like medical records, test results, and imaging investigations to produce a range of possible diagnoses [13].

Medical information systems are utilized in various settings in Kazakhstan, such as hospitals, clinics, and private practices [14]. According to decree of the Minister of Health of the Republic of Kazakhstan dated August 6, 2021 №80, registered with the Ministry of Justice of the Republic of Kazakhstan on August 10, 2021 № 23926. There is about approval of the minimum requirements for medical information systems in the field of healthcare [14].

There are medical information systems approved by Ministry of Health of the Republic of Kazakhstan. There is a list of systems that used in Kazakhstan [15]. According to that list, there are 31 systems; however it was not possible to find a description of all systems. Therefore, 19 systems described in this research paper. There is a table that represents comparative analysis of the main features of the systems (see table 1).

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Table 1. Comparative analysis of the medical information systems

| Name\|Features | Electronic document management, Cloud storage | Appointment: Online Reception Schedule Management | Maintenance of electronic medical records | Finance Services | Calling a doctor at home | Issuing referrals for tests | Diagnosis of diseases online |
|---|---|---|---|---|---|---|---|
| «Info- TRACKER» [16] | + | | + | | | + | |
| «Komek 103» [17] | | | + | | + | | |
| e-clinic Sunkar [18] | + | | + | + | | | |
| InfomedKazakhstan [19] | + | + | + | + | | | |
| KazMedGIS [20] | + | + | + | | + | | |
| IS «BARS» [21] | + | | | | | | |
| IS«InfoDonor» [22] | + | | + | | | + | |
| IS«Komek» 112 [23] | | | | | + | | |
| MIS «Avicenna» [24] | + | | | + | | | |
| MIS«Damumed» [25] | + | + | + | + | | | |
| MISMedElement [26] | + | + | | + | + | | |
| MISAkgun [27] | + | | | + | | | |
| MIS«NfSoft» [28] | + | | + | + | | + | |
| MIS«Ariadna» [29] | + | | + | + | | | |
| MIS«Zhetysu» [30] | + | + | | | + | | |
| MIS«Medialog» [31] | + | + | + | + | | + | |
| iMedHub [32] | + | | | | | + | + |
| PneumoNet [33] | + | | | | | | + |

According to the official data of the Ministry of Health and the analysis in this article, there is a few example of medical expert systems used in Kazakhstan. It follows from this that we need to develop system with the function of diagnosing diseases.

The advancement of automation within the medical sector has traversed multiple stages, each marking a shift in the utilization of information technology. Literature analysis reveals that automated systems have primarily served the purpose of managing medical facilities and processing statistical data. Despite medical cybernetics' initial focus on developing diagnostic systems to facilitate the management of diagnostic and treatment procedures, the methods employed relied on analyzing data pertaining to groups of patients with diverse pathologies [34]. These systems typically provided physicians with solutions presented either as definitive and unequivocal conclusions or as probabilistic assessments of potential diagnoses.

**Optimization methods in medical research**

The human body operates as a intricate system where diverse and sometimes unpredictable processes unfold. As per the International Classification of Diseases (ICD-11) [35], there exist over 50,000 diseases and more than a million symptoms that characterize them. Hence, it becomes paramount for modern medical diagnostic systems to effectively handle such extensive datasets and deliver appropriate solutions to assigned tasks.

The diagnosis of diseases represents a multifaceted procedure necessitating consideration of numerous factors, ranging from external symptoms to comprehensive patient examinations. Factors such as medical history, genetic predispositions, living conditions, among others, also play pivotal roles. Accurately recording this plethora of data facilitates more precise diagnoses and the selection of effective treatments.

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The development of such systems requires the creation of heuristic methods capable of analyzing disease symptoms and establishing mathematical rules for their diagnosis [36]. Examining the outcomes of various medical and biological observations and investigations using mathematical analysis provides new possibilities. This method of addressing issues in medicine is crucial and productive.

The mathematical models use fuzzy set theory and optimization strategies to improve diagnosis accuracy. Fuzzy set theory is useful for dealing with the imprecision and ambiguity that can be found in medical diagnosis, especially when symptoms are not consistently or clearly exhibited by all patients [37]. This theory advocates for representing symptoms and their intensity on a continuous scale rather than as distinct or separate conditions, enabling a more detailed analysis of patient information. These models are applied using matrix diagnostic tables to systematically arrange and correlate symptoms with possible diseases, and to quantify symptom intensity. This methodical technique helps in precisely diagnosing disorders with similar symptoms but necessitating distinct treatments, including differentiating between forms of shock or between conditions causing acute circulatory failure.

Developing expert systems in medicine helps establish clear basic concepts, create study-appropriate models, and clarify the essential principles of the systems under investigation. Developing new mathematical diagnostic models for diseases based on optimization theory methods (such as gradient projection method, method for qualitative uncertainty, etc.) is relevant. Optimization methods allow for the use of not only numerical values but also linguistic variables, which are often medical data used in disease diagnosis (see table 2). Within the scope of expert systems in medicine, the proposed work is relevant and contributes significantly to this field [38]. The research highlights the application of the matrix method of specifying a diagnostic algorithm, as proposed by V.V. Parin [38], in the context of expert systems for disease diagnosis. This adaptation signifies a methodological advancement, showing that traditional matrix methods can be integrated into modern expert systems to enhance their diagnostic processes and outcomes.

Table 2. The matrix method of specifying a diagnostic algorithm

| Symptoms | Diagnosis | | | |
|---|---|---|---|---|
| | Heart attack | Shock (thirddegree) | Perforatedperitonitis | Acutecirculatoryfailure |
| Chest pain | 1 | 0 | 0 | 1 |
| Abdominalpain | 0 | 0 | 1 | 0 |
| Fever | 1 | 0 | 1 | 0 |
| Hypothermia | 0 | 1 | 0 | 0 |
| Leukocytosis | 1 | 0 | 1 | 0 |
| Arrhythmia | 1 | 0 | 0 | 0 |
| Hypertension | 1 | 0 | 0 | 0 |
| Hypotension | 0 | 1 | 1 | 1 |
| Frictionrub | 1 | 0 | 0 | 0 |
| Changes in electrocardiogram | 1 | 0 | 0 | 0 |
| Palenessofskin | 0 | 1 | 1 | 1 |
| General lethargy | 0 | 1 | 1 | 0 |
| Increasedpulserate | 0 | 1 | 1 | 1 |
| Increasedrespiratoryrate | 0 | 1 | 0 | 1 |
| Depressed reflexes | 0 | 1 | 0 | 0 |
| Abdominalwalltension | 0 | 0 | 1 | 0 |
| Cardiacenlargement | 0 | 0 | 0 | 1 |
| Muffledheartsounds | 1 | 0 | 0 | 1 |

The table 2 should be represented in the form (see table 3). Where A1- Heart attack, A2- Shock (third degree), A3- Perforated peritonitis, A4- Acute circulatory failure, with the state of the system determined by $X_j$, $j=1,n$ respectively indicating: chest pain; cardiac arrhythmia; elevated blood pressure; electrocardiogram changes; general lethargy and increased respiratory rate.

Table 3. Matrix form for symptoms and diagnoses

| | | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | X11 | X12 | X13 | X14 | X15 | X16 | X17 | X18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| U | A1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| | A2 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| | A3 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 |
| | A4 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 |

According to the table above, for ease of interpretation, let's represent units in the matrix as the number 9 (in the decimal system), indicating clear superiority, and zeros as the digit 1, as absolute absence of symptoms for the corresponding disease is impossible.

**Project gradients method**

We will use the process of generating gradients to identify the most probable disease for a given set of symptoms in order to make a diagnosis. This method enables you to evaluate the seriousness of symptoms. Table 4 represents the patient's symptoms, data taken from diagnostic table 3.

Table 4. Matrix of symptoms for case example

| | | X1 | X6 | X7 | X10 | X12 | X14 |
|---|---|---|---|---|---|---|---|
| Heartattack | A1 | 9 | 9 | 9 | 9 | 1 | 1 |
| Shock (thirddegree) | A2 | 1 | 1 | 1 | 1 | 9 | 9 |
| Perforatedperitonitis | A3 | 1 | 1 | 1 | 1 | 9 | 1 |
| Acutecirculatoryfailure | A4 | 9 | 1 | 1 | 1 | 1 | 9 |

Let's record the patient's condition as follows: X~={0.7/X1, 0.4/X6, 0.7/X7, 0.5/X10, 0.5/X12, 0.4/X14}. The values 0.4, 0.5, and 0.7 represent the severity of specific symptoms, and the fuzzy utility of options for a given circumstance are extracted from the matrix provided. The severity of the symptom is assessed by the patient, who describes the level of pain on a scale from 0.1, indicating mild discomfort, to 0.9, signifying severe pain. Take a look at the following matrix to see how we might depict the patient's condition A:

$$A = \begin{pmatrix} a_{1x1} & a_{1x6} & a_{1x7} & a_{1x10} & a_{1x12} & a_{1x14} \\ a_{2x1} & a_{2x6} & a_{2x7} & a_{2x10} & a_{2x12} & a_{2x14} \\ a_{3x1} & a_{3x6} & a_{3x7} & a_{3x10} & a_{3x12} & a_{3x14} \\ a_{4x1} & a_{4x6} & a_{4x7} & a_{4x10} & a_{4x12} & a_{4x14} \end{pmatrix} = \begin{pmatrix} 9 & 9 & 9 & 9 & 1 & 1 \\ 1 & 1 & 1 & 1 & 9 & 9 \\ 1 & 1 & 1 & 1 & 9 & 1 \\ 9 & 1 & 1 & 1 & 1 & 9 \end{pmatrix}$$

and

$$\text{Vector}\,\vec{C} = \begin{pmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \end{pmatrix} = \begin{pmatrix} C_1 = 0.7 \\ C_2 = 0.4 \\ C_3 = 0.7 \\ C_4 = 0.5 \\ C_5 = 0.5 \\ C_6 = 0.4 \end{pmatrix} \quad \vec{X} = A = \begin{pmatrix} a_{1x1} & a_{1x6} & a_{1x7} & a_{1x10} & a_{1x12} & a_{1x14} \\ a_{2x1} & a_{2x6} & a_{2x7} & a_{2x10} & a_{2x12} & a_{2x14} \\ a_{3x1} & a_{3x6} & a_{3x7} & a_{3x10} & a_{3x12} & a_{3x14} \\ a_{4x1} & a_{4x6} & a_{4x7} & a_{4x10} & a_{4x12} & a_{4x14} \end{pmatrix} * \vec{C} = \begin{pmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \end{pmatrix}$$

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$$A_1 = X_1 = a_{1x1} * C_1 + a_{1x6} * C_2 + a_{1x7} * C_3 + a_{1x10} * C_4 + a_{1x12} * C_5 + a_{1x14} * C_6 = 9*0.7 + 9*0.4 +$$
$$+ 9*0.7 + 9*0.5 + 1*0.5 + 1*0.4 = 21.6$$

Perform calculations consistently:

$$A2 = X_2 = a_{2x1} * C_1 + a_{2x6} * C_2 + a_{2x7} * C_3 + a_{2x10} * C_4 + a_{2x12} * C_5 + a_{2x14} * C_6 = 10.4$$

$$A3 = X_3 = a_{3x1} * C_1 + a_{3x6} * C_2 + a_{3x7} * C_3 + a_{3x10} * C_4 + a_{3x12} * C_5 + a_{3x14} * C_6 = 7.2$$

$$A4 = X_4 = a_{4x1} * C_1 + a_{4x6} * C_2 + a_{4x7} * C_3 + a_{4x10} * C_4 + a_{4x12} * C_5 + a_{4x14} * C_6 = 12$$

The highest number obtained from the $A_1$; $A_2$; $A_3$; $A_4$ computations indicates that the patient has disease $A_1$ – heart attack.

Therefore: ($\mu$ (Aio))=max (21.6; 10.4; 7.2; 12).

Due to: A(*)= $\mu\sim$ (A1o)=21.6 , The most suitable choice probably illness A1. The diagnosis is a heart attack based on the observed symptoms in the patient and the severity of the symptoms.

**Fuzzysetmethod**

Diagnose using the fuzzy set method incorporating qualitative uncertainty. Identify the most probable condition based on the symptoms presented. This strategy also enables consideration of symptom severity [39]. Based on the table provided above, the ratio: $\mu = \mu_1 + \mu_2 + \ldots + \mu_k$ and $\mu_1 + \mu_2 = \mu_1 + \mu_2 - \mu_1 * \mu_2$. (If an element in the domain occurs K times)

$$\tilde{U}_{ij} = \bigcup_k \mu_{u_{ij}}(u_k)/u_k, \quad \text{where} \quad u_k = \mu \sim (x_k) \tag{1}$$

Using formula (1) perform calculations consistently:

$U_1$ = {0.7/9; 0.4/9; 0.7/9; 0.5/9; 0.5/1; 0.4/1} = {0.973/9; 0.7/1};
$U_2$ = {0.973/1; 0.7/9}; $U_3$ = {0.98/1; 05/9}; $U_4$ = {0.82/9; 0.955/1}

Maximizing sets:

$U_{1m}$ = {9:9/9; 1:9/1}= {1/9; 0.11/1};$U_{2m}$= {9:9/9; 1:9/1} = {1/9; 0.11/1};
$U_{3m}$= {9:9/9; 1:9/1} = {1/9; 0.11/1};$U_{4m}$ = {9:9/9; 1:9/1} = {1/9; 0.11/1}.

$$\mu_{\underset{u_i}{\sim}}(\tilde{u}_k) = \min\,[\mu_{\tilde{x}}(\tilde{x}_k),\ \mu_{\tilde{u}_{ik}}(u_i)] \tag{2}$$

Minimization leads to a reduced risk of misdiagnosis.Optimizing sets calculated by formula (2).

$U_{1o}$ = {min (0.973, 1); min (0.7, 0.11)} = {0.973; 0.11};
$U_{2o}$ = {min (1, 0.7); min (0.973, 0.11)} = {0.7; 0.11};
$U_{3o}$ = {min (0,5,1); min (0.98, 0.11)} = {0.5; 0.11/1};
$U_{4o}$ = {min (1, 0.82); min (0.955, 0.11)} = {0.82, 0,11};

Then ($\mu$ (Aio))=max (0.973; 0.7; 0.5; 0.82) .

Due to: A(*)= $\mu\sim$ (A1o)= 0.973, In that case, the best possible alternative is illness. A1. The diagnosis is a heart attack, taking into consideration the range of symptoms that have been observed in the patient as well as the current state of the system (the degree of severity of the symptoms).

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**Proposed method**

A different approach to displaying a database is proposed by us. Specifically, we propose replacing the utilities in the table (using the matrix method) with linguistic variables that are frequently seen in the field of medicine (usually, possibly seldom, etc.). When it comes to the matrix approach for diseases: utility, experts believe that one can be substituted for the concept typical, and zeros are extremely rare. We represent these concepts in the form below:

$$T\ (\text{typical})=\{0.5/8;\quad 1.0/9\};\quad ER\ (\text{extremely rare})=\{0.5/2;1.0/1\}.$$

Table5. Matrix of patients' symptoms with linguistic variables

| | X1 | X6 | X7 | X10 | X12 | X14 |
|---|---|---|---|---|---|---|
| Heartattack | T | T | T | T | ER | ER |
| Shock (thirddegree) | ER | ER | ER | ER | T | T |
| Perforatedperitonitis | ER | ER | ER | ER | T | ER |
| Acutecirculatoryfailure | T | ER | ER | ER | ER | T |

Patient's condition: $X\sim=\{0.7/X1, 0.4/X6, 0.7/X7, 0.5/X10, 0.5/X12, 0.4/X14\}$. To facilitate the comparison of the benefits of both methods, we will use the same level of symptom severity as in the previous method. Let's enter the values of linguistic variables: $U_1=\{0.7/T; 0.4/T; 0.7/T; 0.5/T; 0.5/ER; 0.4/ER\}= \{0.93/T; 0.7/ER\}$;

Then calculations are done by formula 1:

$U_1 = \{0.93/T; 0.7/ ER\}=\{0.93/[0.5/8; 1.0/9]; 0.7/[0.5/2;1.0/1]\}$

$U_2 = \{0.93/ ER; 0.7/ T\}=\{0.93/[0.5/2;1.0/1]; 0.7/[0.5/8; 1.0/9]\}$

$U_3 = \{0.98/ ER; 05/ T\}=\{0.98/[0.5/2;1.0/1]; 0.5/[0.5/8; 1.0/9]\}$

$U_4 = \{0.82/ T; 0.955/ ER\}=\{0.82/[0.5/8; 1.0/9]; 0.955/[0.5/2;1.0/1]\}$

Then let's streamline: $U_1=\{\min (0.93, 0.5)/8; \min (0.93, 1.0)/9]; \min (0.7, 0.5)/2; \min (0.7, 1)//1]\} = \{0.5/8; 0.973/9; 0.5/2; 0.7/1\}$;

$U_2=\{0.5/2; 0.93/1; 0.5/8; 0.7/9\}$;

$U_3 = \{0.5/2; 0.98/1; 0.5/8; 0.5/9]\}$;

$U_4= \{0.5/8; 0.82/9; 0.5/2; 0.955/1\}$

Maximizing sets:

$U_{1m} = \{8:9/8; 9:9/9: 2:9/2; 1:9/1\}= \{0.88/8; 1/9; 0.22/2; 0.11/1\}$;

$U_{2m} = \{2:9/2; 1:9/1: 8:9/8; 9:9/9\}= \{0.22/2; 0.11/1; 0.88/8; 1/9;\}$

$U_{3m} = \{0.22/2; 0.11/1; 0.88/8; 1/9\}$

$U_{4m} = \{0.88/8; 1/9; 0.22/2; 0.11/1\}$

Optimizing sets:

$U_{1o} = \{(\min (0.88, 0.5)/8; \min (0.93, 1)/9; \min (0.22, 0.5)/2; \min (0.7, 0.11)/1\}=\{0.5/8, 0.93/9\}$

$U_{2o}= \{(\min (0.5, 0.22)/2; \min (0.93, 0.11)/1; \min (0.88, 0.5)/8; \min (1, 0.6)/9\}=\{0.22 /2; 0.11/1, 0.5/8, 0.6/9\}$

$U_{3o} = \{0.22/2; 0.11/1; 0.5/8; 0.5/9\}$

$U_{4o} = \{0.5/8; 0.82/9; 0.22/2; 0.11/1\}$

Finally: $A(*)= \mu\sim (A_{1o})= 0.93$.

$A(*)= \mu\sim (A_{1o})= 0.93$ same result heart attack. The coincidence suggests that mathematical approaches can be used to diagnose disorders in medicine. However, the format of the database is presented in different way (linguistic variables, qualitative uncertainty,and binary form).

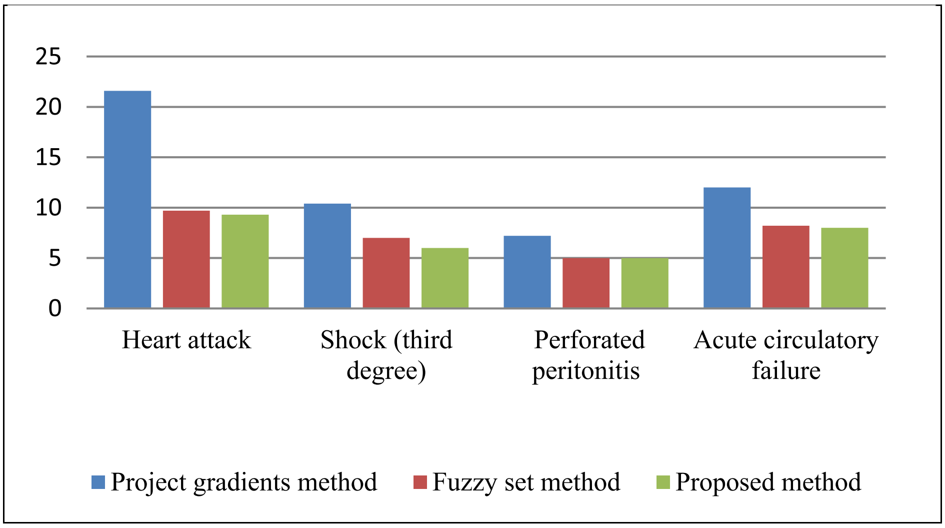


Figure 2. An examination of three distinct diagnostic approaches for severe medical conditions across different scoring or measurement systems.

The diagram presents a comparison of three different diagnostic methods for various severe medical conditions, based on some form of scoring or measurement (fig. 2). The methods compared are the Project gradients method; the Fuzzy set method, and a proposed method.

The Project gradients approach consistently outperforms the Fuzzy set method and the proposed method in all scenarios, suggesting a potentially higher sensitivity or a different measuring scale. Both the Fuzzy set approach and the Proposed method demonstrate comparable scores across all conditions, with the Fuzzy set method significantly outperforming in cases of heart attack and acute circulatory failure. It can be inferred that all three procedures yielded identical results. A heart attack was detected with similar symptoms but using a different diagnostic approach [39].

The following procedure is followed in order to arrive at a diagnosis (fig 3): initial data with the help of a diagnostic table; diagnostic model with the assistance of mathematical methods; preliminary diagnosis with the help of probabilistic methods; - further examination (if it seems to be required); The ultimate diagnosis is the doctor’s top priority.

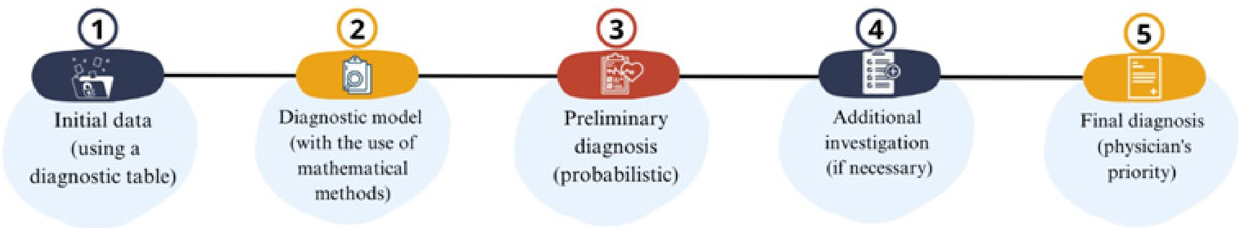


Figure 3. Diagnosing procedure algorithm

Through the use of optimization theory methods, new mathematical models for disease diagnosis have been established. These methods include the gradient projection method, the method under qualitative uncertainty, and others. When compared to models such as Bayes’ approach, which are utilized in the medical field, the mathematical models that were developed have a number of advantages in terms of disease diagnosis [39]. In the study, it was demonstrated that the mathematical model that was developed based on fuzzy set theory and optimization methods uses both matrix diagnostic tables and the degree of symptom severity for the purpose of diagnosing diseases. These diseases include heart attack, shock (third degree), perforated peritonitis, and acute circulatory failure. Because of this, new opportunities have arisen for the development of automated illness diagnostic complexes, which will be an essential component of the medical system of the future.

Integrating these mathematical models into healthcare has the potential to greatly enhance diagnostic processes. They can aid in promptly and precisely detecting diseases, especially critical for circumstances necessitating urgent care, such as heart attacks and serious infections like perforated peritonitis. Furthermore, automating diagnostic procedures using these models can improve the effectiveness of healthcare systems by decreasing the time and resources required for diagnosis, enabling quicker treatment.

This progress in medical diagnostics signifies a shift towards personalized and precise medicine, allowing therapies to be more accurately customized for specific patients through detailed studies of their symptoms and diseases [40]. The increasing significance of multidisciplinary collaboration in healthcare is highlighted, as mathematical, computational, and medical knowledge are used to tackle intricate health issues.

**Discussions**

Diagnostic expert systems offer *benefits* such as enhanced precision, quicker diagnosis, and the capacity to offer details on diagnostic tests and treatments, surpassing traditional diagnostic approaches. They can also be utilized in settings with limited resources when access to specialized medical knowledge may be scarce.

However, diagnostic expert systems have *limitations* that must be considered. They rely on the precision and thoroughness of the data they get and might not be equipped to handle uncommon or intricate scenarios. Furthermore, they might not always provide a definitive diagnosis, requiring further testing and evaluations to confirm a diagnosis.

Although limited, diagnostic expert systems are a significant tool for healthcare workers in diagnosing various disorders. They can enhance patient outcomes and lower healthcare costs by decreasing the time and resources needed for precise diagnoses.

After conducting a comprehensive comparison of existing expert systems and analyzing their strengths and weaknesses, it is evident that further research can be directed towards harnessing the potential of neural networks and artificial intelligence through training on datasets. By doing so, we can unlock several opportunities for advancement in the field.

*Possible research directions* include enhancing diagnostic accuracy by utilizing neural networks to analyze large medical datasets. This entails improving current models or creating new structures customized for medical diagnostics.Investigate the use of neural networks to provide individualized therapy suggestions by training them on various patient datasets. Utilize patient-specific traits, genetic data, and treatment background to enhance medical interventions.Explain the application of AI in healthcare. Improve the comprehensibility of neural network models to offer justifications for their predictions. Create approaches that clarify the factors and decision-making processes of the models, helping healthcare professionals understand and have confidence in the suggestions produced.

Investigate methods to address uncertainty and variability in medical datasets. This could entail incorporating probabilistic models, Bayesian methodologies, or ensemble techniques to produce more dependable forecasts and address inherent uncertainties in medical data.

Develop neural network models to offer real-time decision help to healthcare practitioners. This involves creating effective algorithms capable of analyzing data in real-time to allow for prompt actions and enhance patient results.

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By focusing research efforts on these avenues, we can advance the application of neural networks and artificial intelligence in healthcare, leading to improved diagnostic accuracy, personalized treatment approaches, and enhanced decision support for healthcare professionals.

**Conclusion**

The field of healthcare decision support systems is extensive and has a rich history, with numerous systems presumably built and utilized for this purpose in the past.

Healthcare decision support systems are designed to aid in medical decision-making, enhance patient outcomes, and increase the effectiveness of healthcare systems. They usually utilize a blend of algorithms, statistical models, and medical expertise to offer advice and suggestions to healthcare providers. Decision support systems are gaining popularity in healthcare due to their data-driven and methodical approach to decision-making, which helps address the shortcomings of previous methods.

These systems have significantly influenced the development of medical decision-making and remain crucial in the healthcare sector. Various diagnostic methods are utilized globally, with a few specific examples employed in Kazakhstan. Any diagnostic system must be tailored for Kazakhstan population. Hence, creating a diagnostic system for inhabitants of Kazakhstan is a current priority.

Medical information systems are significantly enhancing the precision and effectiveness of diagnosis in Kazakhstan. By consolidating data from many sources and offering immediate assistance to medical practitioners, these technologies are enhancing patient results and lowering healthcare expenses.

An important outcome of the study is that expert systems have the capability to effectively diagnose critical situations using different data inputs and procedures, as demonstrated by the fact that all three types of diagnostic tables can be utilized to characterize a heart attack. This exemplifies the capacity of the systems to successfully integrate and evaluate diverse forms of data in order to arrive at a definitive diagnosis.The successful application of these diverse methods and diagnostic inputs in diagnosing heart attacks suggests that expert systems can be designed or modified to incorporate a variety of diagnostic algorithms and data types. This flexibility is crucial for developing more effective, accurate, and comprehensive diagnostic tools in the medical field.

The utilization of mathematical tools suggested within the research, alongside their integration into automated disease diagnostic systems, presents extensive opportunities for further investigation and enhancement of medical procedures. Employing mathematical methodologies in automated disease diagnosis systems showcases a notable enhancement in diagnostic efficiency and precision relative to conventional approaches. Mathematical models and algorithms enable a more precise identification of pathologies and the determination of diagnoses through the analysis of extensive datasets, thus mitigating the risk of diagnostic inaccuracies. The developed tools facilitate the automation of diagnostic procedures, expediting result delivery and streamlining the tasks of medical professionals.

Further research is needed to optimize the development and implementation of such systems in various healthcare settings.In summary, the research contributes to the advancement of diagnostic expert systems by demonstrating the effective use of various diagnostic table types and methodologies, including the innovative application of the matrix method, to accurately diagnose diseases. This versatility and methodological innovation pave the way for further development of expert systems capable of handling complex and varied medical diagnostic challenges.

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