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HIERARCHICAL MACHINE LEARNING SYSTEM FOR FUNCTIONAL DIAGNOSIS OF EYE PATHOLOGIES BASED ON THE INFORMATION-EXTREMAL APPROACH

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ABSTRACT

Context. The task of information-extremal machine learning for the diagnosis of eye pathologies based on the characteristic signs of diseases is considered. The object of the study is the process of hierarchical machine learning in the system for diagnosing ophthalmological diseases. The aging population and the increasing prevalence of eye diseases, such as glaucoma, optic nerve atrophy, retinal detachment, and diabetic retinopathy, necessitate effective methods for early diagnosis to prevent vision loss. Traditional diagnostic methods largely rely on the experience of the physician, which can lead to errors. The use of artificial intelligence (AI) and machine learning (ML) can significantly improve the accuracy and speed of diagnosis, making this topic highly relevant.

Objective. To enhance the functional efficiency of a computerized system for diagnosing eye pathologies based on image data.

Method. A method of information-extremal hierarchical machine learning for a system of eye pathology diagnosis based on the characteristic signs of diseases is proposed. The method is based on a functional approach to modeling cognitive processes of natural intelligence, ensuring the adaptability of the diagnostic system under any initial conditions for the formation of pathology images and allowing flexible retraining of the system when the recognition class alphabet expands. The foundation of the method is the principle of maximizing the criterion of functional efficiency based on a modified Kullback information measure, which is a functional of the diagnostic rule precision characteristics. The learning process is considered as an iterative procedure for optimizing the parameters of the diagnostic system's operation according to this information criterion. Based on the proposed categorical functional model, an information-extremal machine learning algorithm with a hierarchical data structure in the form of a binary recursive tree is developed. This data structure enables the division of a large number of recognition classes into pairs of nearest neighbors, for which the machine learning parameters are optimized using a linear algorithm of the necessary depth.

Results. An intelligent technology for diagnosing eye pathologies has been developed, which includes a comprehensive set of information, algorithmic, and software components. A comparative analysis of the effectiveness of different methods for organizing decision rules during system training has been conducted. It was found that the use of recursive hierarchical classifier structures allows achieving higher diagnostic accuracy compared to binary classifiers.

Conclusions. The developed intelligent computer-based diagnostic system for eye pathologies demonstrates high efficiency and accuracy. The implementation of such a system in medical practice could significantly improve the quality of eye disease diagnostics, reduce the workload on physicians, and minimize the risk of misdiagnosis. Further research could focus on refining algorithms and expanding their application to other types of medical images.

KEYWORDS: computer diagnosis of eye pathologies, artificial intelligence, machine learning, image processing, pattern recognition, information-extremal technology, hierarchical classifier structure.

ABBREVIATIONS

IEI-technology – information-extremal intelligent technology;

SCT – system of control tolerances;

AI – artificial intelligence;

DL – deep learning;

ML – machine learning;

ODS – ophthalmological diagnostic system.

NOMENCLATURE

M is a power of the alphabet of diagnostic classes;

m is a number of the current classes of ophthalmic diagnostics;

N is a power of the dictionary of diagnostic features;

i is a number of the diagnostic feature;

n is a volume of the training matrix of diagnostic classes;

j is a number of the structured vector of diagnostic feature values in the training matrix;

H is a set of strata in the de-recursive tree;

h is a number of the stratum in the de-recursive tree;

S is a set of strata in the de-recursive tree;

s is a number of the stratum in the de-recursive tree;

$x_{0,i}^{(h,s)}$ is an averaged feature vector of the base diagnostic class $x_0^{(h,s)}$ at the h-th level of the s-th stratum of the de-recursive tree;

$x_{1,i}^{(h,s)}$ is an averaged feature vector of the class nearest to the base diagnostic class $x_1^{(h,s)}$ at the h-th level of the s-th stratum of the de-recursive tree;

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$d_0^{(h,s)}$ is a radius of the hyperspherical container of the base diagnostic class $x_0^{(h,s)}$;

$d_1^{(h,s)}$ is a radius of the hyperspherical container of the class nearest to the base diagnostic class $x_1^{(h,s)}$;

K is a set of machine learning steps;

$\delta_{K,i}^{(h,s)}$ is a parameter equal to half of the control tolerance field for the features of the diagnostic classes at the h-th level of the s-th stratum;

G_E is a working (permissible) domain for the definition of the information optimization criterion function;

$G_{d_0^{(h,s)}}$ is a permissible domain of the radius values for the container of the base diagnostic class $x_0^{(h,s)}$ at the h-th level of the s-th stratum;

$G_{d_1^{(h,s)}}$ is a permissible domain of the radius values for the container of the class nearest to the base diagnostic $x_1^{(h,s)}$ class at the h-th level of the s-th stratum;

$E_0^{(h,s)}$ is an information criterion for optimizing the machine learning parameters for the base diagnostic class $x_0^{(h,s)}$;

$E_1^{(h,s)}$ is an information criterion for optimizing the machine learning parameters for the class nearest to the base diagnostic class $x_1^{(h,s)}$;

G is a set of input factors that influence the ODS;

T is a set of moments in time for reading the information;

Ω is a feature space for diagnostics;

Z is a set of technical states of the diagnostic object;

$Y^{(h,s)}$ is a input training matrix of the diagnostic classes at the h-th level of the s-th stratum of the de-recursive tree;

$X^{(h,s)}$ is a binary training matrix of the diagnostic classes at the h-th level of the s-th stratum of the de-recursive tree;

f_0 is an operator for forming the de-recursive binary trees H;

f_1 is an operator for forming the training matrix $Y^{(h,s)}$;

f_2 is an operator for forming the binary training matrices $X^{(h,s)}$;

$d_0^{*(h,s)}$ is an optimal radius of the hyperspherical container of the base diagnostic class $x_0^{(h,s)}$;

$d_1^{*(h,s)}$ is an optimal radius of the hyperspherical container of the class nearest to the base diagnostic class $x_1^{(h,s)}$;

$X_m^{o(h,s)}$ is a container of the diagnostic class at the h-th level of the s-th stratum of the de-recursive tree;

$I_{0,m}^{(h,s)}$ is a set of statistical hypotheses for the decision rule of the base diagnostic class $x_m^{(h,s)}$;

$I_{1,m}^{(h,s)}$ is a set of alternative hypotheses for the decision rule of the class nearest to the base diagnostic class $x_m^{(h,s)}$;

ψ is an operator for testing the main statistical hypothesis about the assignment of the vector $x_m^{(h,s)}$ to the diagnostic class $X_m^{o(h,s)}$;

γ is an operator for forming the set of accuracy characteristics;

ζ is an operator for forming the set of reference vector values and optimal radii;

$D_1^{h,s}$ is an extreme value of the first reliability at the h-th level of the s-th stratum of the de-recursive tree;

$D_2^{h,s}$ is an extreme value of the second reliability at the h-th level of the s-th stratum of the de-recursive tree;

$\alpha^{h,s}$ is a first-type error, calculated at the h-th level of the s-th stratum of the de-recursive tree;

$\beta^{h,s}$ is a second-type error, calculated at the h-th level of the s-th stratum of the de-recursive tree;

φ_1 is an operator for forming the value of the optimization criterion $E_1^{(h,s)}$ and $E_0^{(h,s)}$;

φ_2 is an operator for forming the value of the total optimization criterion $\overline{E}^{(h,s)}$;

u is an operator that regulates the machine learning process;

r is an operator for partitioning Ω the diagnostic feature space into classes;

f_H is an operator that regulates the process of forming and evaluating the functional efficiency of the strata in the de-recursive tree;

$\rho_{m,i}$ is a selection level;

$\otimes$ is a symbol for the repetition operation;

d is a parameter that characterizes the radius values of the diagnostic class containers in code units;

10^{-p} is a sufficiently small number introduced to avoid division by zero (in practice, it is taken as $p = 2$);

$x^{(j)}$ is a structured vector of diagnostic feature values, formed during the stage of diagnostic decision-making;

μ_m is a membership function of vector $x^{(j)}$ for the diagnostic class $X_m^{o,(h,s)}$.

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INTRODUCTION

Modern medicine faces numerous challenges, among which the tasks of diagnosing and treating eye diseases stand out [1]. With the growing number of patients with ophthalmic problems such as optic nerve atrophy, glaucoma, retinal detachment, and diabetic retinopathy, there is a need for the development of new, more effective diagnostic methods [2, 3]. Traditional diagnostic methods, based on visual assessment of fundus images and other examinations, largely depend on the subjective evaluation of the physician, which can lead to errors and inaccuracies.

Currently, the widespread use of AI and ML technologies in computerized diagnostic systems allows for a significant acceleration of medical image processing and an increase in the accuracy of pathology detection, providing effective support for medical professionals in clinical decision-making. Priority is given to artificial neural network technology, as it is believed to be capable of effectively processing large volumes of medical data, ensuring high accuracy in detecting patterns and anomalies in medical images [4–6]. An alternative to the use of artificial neural networks is information-extreme intellectual technologies, the effectiveness of which has been proven in solving many practical problems across various tasks [7–9].

The object of the research is the process of hierarchical machine learning in the system of functional diagnosis of ophthalmic diseases.

The subject of the research is the methods for building and optimizing the system of information-extreme hierarchical machine learning for diagnosing eye pathologies based on images.

The purpose of the work is to develop an IEI technology for computerized diagnosis of eye pathologies. Such a technology should include modern image processing and pattern recognition methods, as well as utilize machine learning algorithms to improve diagnostic accuracy.

The article discusses the main stages of developing and implementing this technology, starting from the analysis of existing methods and ending with the creation of software and its testing on real medical data. It is expected that the results of this research will contribute to improving the quality of medical care and serve as a foundation for further research in the field of medical diagnostics.

1 PROBLEM STATEMENT

Let us consider the formalized formulation of the information synthesis task for a ODS capable of learning based on images of human eye pathologies.

Let the alphabet $\{X_m^o \mid m=\overline{1,M}\}$, of diagnostic classes be given, which is formed according to the main diseases of the human visual organs. The peculiarities of ophthalmic diagnostics, which include visual examination and fundus scanning, allow the use of its images to form a training matrix $\| y_{m,i}^{(j)} \mid i=\overline{1,N}; j=\overline{1,n} \|$. In this case $\left\{ y_{m,i}^{(j)} \mid i=\overline{1,N} \right\}$, a row of the matrix represents the j-th realization, and a column $\left\{ y_{m,i}^{(j)} \mid j=\overline{1,n} \right\}$ represents the training sample of values for the i-th diagnostic feature.

According to the concept of IEI-technology, the input training matrix is transformed during deep machine learning into a set of diagnostic decision rules, the parameters of which are optimized (in the informational sense) by maximizing the functional efficiency of the ODS. Let the depth of machine learning be two levels. At the first level, the optimal phenotypic parameters of the ODS are determined, namely the geometric parameters of the hyperspherical containers of diagnostic classes, and at the second level, the genotypic parameters, namely the system of control tolerances for diagnostic features, are determined. The structured vector of parameters influencing the functional efficiency of deep machine learning in the ODS is as follows:

$$g^{(h,s)} = \left\langle \left\{ x_{0,i}^{(h,s)} \right\}, d_0^{(h,s)}, \left\{ x_{1,i}^{(h,s)} \right\}, d_1^{(h,s)}, \left\{ \delta_{K,i}^{(h,s)} \right\} \right\rangle \quad (1)$$

with the corresponding constraints [7] to the strata of the recursive hierarchical structure of pairs of nearest neighboring diagnostic classes.

During the machine learning process in the ODS, it is necessary to:

1) optimize the parameters of the vector (1) for each stratum of the hierarchical structure of diagnostic classes:

$$E^{(h,s)} = \frac{\max\limits_{G_E \cap G_{d_0^{(h,s)}}} E_0^{(h,s)}\left(d_0^{(h,s)}\right) + \max\limits_{G_E \cap G_{d_1^{(h,s)}}} E_1^{(h,s)}\left(d_1^{(h,s)}\right)}{2}. \quad (2)$$

2) Based on the optimal geometric parameters of the container classes obtained through machine learning, we will construct decision rules for each stratum of the hierarchical structure, ensuring a high probability of making correct diagnostic decisions.

3) At the examination stage, it is necessary to make a diagnostic decision about the assignment of the structured vector of diagnostic feature values to one of the classes in the formed alphabet of the corresponding final stratum.

Thus, the task of information-extreme synthesis of the learnable ODS is to optimize the parameters of its machine learning by approximating the global maximum of the information criterion (2) to its maximum limiting value.

2 REVIEW OF THE LITERATURE

The implementation of AI in the field of medical diagnostics is one of the key trends in the development of modern science. Ophthalmology, as one of the branches of medicine, actively utilizes the potential of AI to improve the accuracy and effectiveness of diagnosing

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ophthalmological diseases, as evidenced by numerous scientific studies.

In connection with the global demographic trend of an aging population, a significant increase in the number of patients suffering from ophthalmological diseases is predicted [1–3]. Timely diagnosis and appropriate treatment are crucial for preventing the progression of ophthalmological diseases and vision loss. Traditional diagnostic methods largely depend on the professional experience of doctors, which can lead to a high frequency of misdiagnoses and loss of medical data. The deep synergy between ophthalmology and artificial intelligence contributes to the creation of innovative methods for processing and analyzing medical data, providing ophthalmologists with powerful tools to enhance the accuracy and speed of diagnostics [4–6].

AI, first proposed by John McCarthy in 1956, became a general term for technologies that mimic intelligent behavior. However, the real breakthrough in the application of AI occurred only recently, thanks to the emergence of new algorithms, specialized hardware, and large volumes of data. ML, as a subfield of AI, encompasses methods for automatically detecting patterns in data and using them to predict future events under conditions of uncertainty [10, 11].

DL, which emerged in the early 21st century, became a catalyst for revolutionary changes in the field of AI. This technology forms the foundation of many modern systems, particularly in tasks such as image recognition, automatic translation, and intelligent control. In healthcare, DL is applied to histopathological analysis, skin cancer classification, cardiovascular disease risk prediction, and lung cancer detection [12–14].

In ophthalmology, AI is actively used for the diagnosis of retinal diseases, glaucoma, diabetic retinopathy, and other pathologies. For example, probabilistic neural networks have been used for analyzing the blood vessels of the retina, while a three-layer artificial neural network and support vector machine methods have been applied for classifying retinal diseases based on fundus images [6, 15, 16].

Intelligent diagnostic systems provide high accuracy, reduce computational costs, and shorten working time, making them indispensable in medical practice. For example, in [17], it was shown that machine learning algorithms can be used for accurately determining the condition of the retina and predicting the development of diseases.

The main advantages of using AI in ophthalmology are the ability to process large volumes of data, automate the diagnostic process, and achieve high accuracy in results. Furthermore, images obtained through slit-lamp examination, visual acuity testing, fundus images, ultrasound imaging, and optical coherence tomography can be stored for further analysis and monitoring [16–18].

Thus, the development of artificial intelligence technologies opens up new opportunities for ophthalmology, providing more accurate and timely diagnosis of eye diseases, which contributes to improving the quality of life of patients and reducing the risks of vision loss.

3 MATERIALS AND METHODS

The method of information synthesis for the ODS will be considered within the framework of the IEI-technology, which is based on maximizing the functional efficiency of the system during deep machine learning. This approach enables the use of both linear and hierarchical structures of diagnostic classes. An essential task within this process is the automation of forming optimal hierarchical structures in the form of a binary de-recursive information tree. Unlike recursive structures, in this case, the attribute from the node of the upper tier is passed to the node of its corresponding stratum in the lower tier. In our approach, the attributes of the nodes are represented by training matrices corresponding to the respective diagnostic classes. The de-recursive hierarchical structure is partitioned into strata, each consisting of two classes with the closest Hamming feature distance in the binary space. This structure enables the application of a linear algorithm of information-extreme machine learning with the required depth for classification. In contrast to neural-like structures, the depth of information-extreme machine learning is determined not by the number of hidden layers, but by the number of machine learning parameters optimized according to an information criterion [7, 9, 19].

The input mathematical description of the ODS is considered as a set-theoretic structure

$$I_B =< G,T,\Omega,Z,H,\, Y^{(h,s)}, X^{(h,s)}, f_0, f_1, f_2 >,$$

and the functional categorical model of information-extreme machine learning based on the hierarchical data structure is represented as a diagram of mappings between these sets by machine learning operators.

The categorical model of information-extreme machine learning for the ODS in stratum s at level h of the de-recursive hierarchical data structure is shown in Fig. 1 [8].

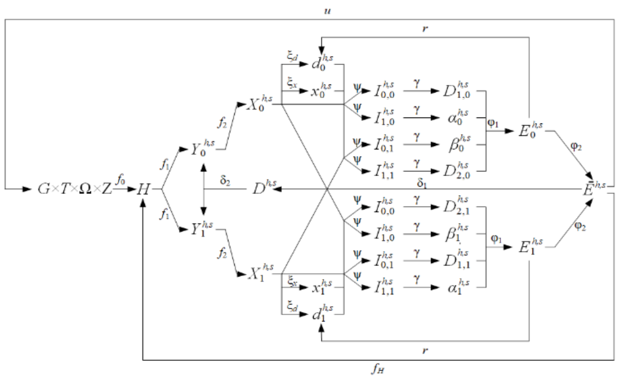

Figure 1 – Categorical Model of Machine Learning for the ODS

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The operator f_0, shown in Fig. 1, originating from the information source defined by the Cartesian product of sets $G \times T \times \Omega \times Z$, generates the de-recursive binary tree H, while the operator f_1 forms the input training matrices for the corresponding strata $Y^{(h,s)}$. The operator f_2, by comparing the values of diagnostic features with their specified tolerance limits, forms the corresponding set $X^{(h,s)}$ of binary working matrices, which, during the machine learning process, are adapted through permissible transformations to achieve the maximum overall probability of making correct classification decisions. The term-set E, whose elements are the values of the information criterion computed at each step of the learning process, is common to all optimization loops of the learning parameters, in accordance with the principle of complete composition. The operator ζ computes the set of reference vector values $x_0{}^{(h,s)}$, $x_1{}^{(h,s)}$ and the optimal radii $d_0^{*(h,s)}$, $d_1^{*(h,s)}$ of the diagnostic class containers $X_m^{o(h,s)}$. The operator $\psi : X_0^{(j)} \in X_0^{(h,s)} \to I_{0,0}^{(h,s)}$, tests the main statistical hypothesis $I_{0,0}^{(h,s)}$ (or $I_{0,1}^{(h,s)}$) and the alternative hypothesis $I_{1,0}^{(h,s)}$ (or $I_{1,1}^{(h,s)}$). The operator γ forms the set of accuracy characteristics $D_1^{h,s}, \alpha^{h,s}, \beta^{h,s}, D_2^{h,s}$, while the operator φ_1 calculates the values of the optimization criterion $E_1^{(h,s)}$ and $E_0^{(h,s)}$ for the neighboring diagnostic states of the human eye. At the same time, the operator φ_2 computes the overall value of the optimization criterion $\overline{E}^{(h,s)}$. The operator $u : \overline{E}^{(h,s)} \to G \times T \times \Omega \times Z$ regulates the machine learning process during the ophthalmological diagnosis of the human eye.

Thus, the proposed categorical model of information-extreme machine learning enables the automatic formation of a de-recursive hierarchical structure of diagnostic classes in real-time.

The implementation of information-extreme machine learning using a hierarchical data structure represented by a binary de-recursive tree is carried out according to the following scheme:

1. Formation of the tolerance field for diagnostic features of stratum s at hierarchical level h:

1.1 Determination of the averaged vector of structured diagnostic features for class $X_0^{o(h,s)}$

$$y_{0,i}^{(h,s)} = \frac{1}{n}\sum_{j=1}^{n} Y_{0,i}^{j(h,s)};$$

1.2 Determination of the upper control tolerance

$$A_{BK,i}^{(h,s)} = y_{0,i}^{(h,s)} + \delta_{K,i}^{(h,s)};$$

1.3 Determination of the lower control tolerance

$$A_{HK,i}^{(h,s)} = y_{0,i}^{(h,s)} - \delta_{K,i}^{(h,s)};$$

2. Formation of the binary training matrix $X^{(h,s)}$

$$X_{m,i}^{j(h,s)} = \begin{cases} 1, \text{ if } A_{HKm,i}^{(h,s)} < Y_{m,i}^{j(h,s)} < A_{BKm,i}^{(h,s)}; \\ 0, \text{ if otherwise;} \end{cases}$$

3. A set $\{x_m^{(h,s)}\}$ of binary averaged vectors of diagnostic features is formed according to the following rule

$$x_{m,i}^{(h,s)} = \begin{cases} 1, \text{ if } \frac{1}{n}\sum_{j=1}^{n} X_{m,i}^{j(h,s)} \geq \rho_{m,i}; \\ 0, \text{ if otherwise;} \end{cases}$$

4. Ranking of $\{x_m^{(h,s)}\}$ by code distance from the zero binary vector and determination of the composition of the two branches of stratum s at level h of the binary de-recursive tree by dividing the set of classes into two approximately equal and non-overlapping groups.

5. Optimization (in the informational sense) of the values of phenotypic and genotypic learning parameters, and derivation of decision rules for the two classes with the smallest code distance $\{x_m^{(h,s)}\}$, belonging to different branches of stratum s at level h.

6. The branching continues until the formation of so-called final strata, the branches of which contain only one diagnostic class each.

Thus, during the formation of strata in the binary de-recursive tree, the optimal set of phenotypic and genotypic learning parameters is obtained for all pairs of the nearest neighboring classes, which is a necessary condition for the pairwise partitioning of the diagnostic feature space by means of information-extreme machine learning using a linear algorithm [20, 21].

According to the categorical model (Fig. 1), the information-extreme machine learning algorithm of the ODS based on a hierarchical data structure is presented as a procedure regulated by operator f_H for searching the global maximum of the criterion (2) averaged over the alphabet $\left\{X^{o(h,s)}\right\}$ of the corresponding diagnostic classes of the stratum:

$$\delta_K^{*(h,s)} = \arg\max_{G_\delta^{(h,s)}} \left\{ \max_{G_E \cap G_d} \overline{E}^{(h,s)}(d) \right\}. \quad (3)$$

Thus, unlike the linear algorithm, in which the optimal value of the parameter δ is determined for the entire

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diagnostic class alphabet, in information-extreme machine learning based on a hierarchical de-recursive data structure, the parameter $\left\{\delta_{K,i}^{(h,s)}\right\}$ is determined separately for each stratum.

The internal loop of procedure (3) implements the basic algorithm, whose functions include calculating the criterion (2) at each step of the machine learning process, searching for its global maximum, and determining the optimal geometric parameters of the diagnostic class containers [21, 22].

$$d_m^{*(h,s)} = \arg\max_{G_E \cap G_d} \overline{E}^{(h,s)}\left(d_m^{(h,s)}\right), m = \overline{1, M^{(h,s)}} . \quad (4)$$

In the outer loop of procedure (3), the operator for adjusting the parameter $\left\{\delta_{K,i}^{(h,s)}\right\}$ of the control tolerance field is executed until the value of the information criterion for optimizing the machine learning parameters reaches its maximum [9, 19].

As the optimization criterion for machine learning parameters of the ODS within each stratum of the de-recursive hierarchical data structure, a modified Kullback information measure was used [7, 23], which, for two equally probable alternative hypotheses, takes the following form:

$$E_m^{(k,h,s)} = \frac{1}{2}\{2-[\alpha_m^{(k,h,s)}(d)+\beta_m^{(k,h,s)}(d)]\}\times$$
$$\times\log_2\frac{2-[\alpha_m^{(k,h,s)}(d)+\beta_m^{(k,h,s)}(d)]+10^{-p}}{\alpha_m^{(k,h,s)}(d)+\beta_m^{(k,h,s)}(d)]+10^{-p}}. \quad (5)$$

The decision rules are constructed in the form of an implication based on the optimal geometric parameters of the hyperspherical containers of the diagnostic classes.

$$(\forall h,s,m)\left(\forall x^{(j)}\in\Omega\right)\left\{if\ d\left(x^{(j)}\oplus\left\{x_{m,i}^{(h,s)}\right\}\right)\le d_m^{(h,s)}\ \&\right.$$
$$\&\left(m^* = \arg\max_{\{m\}}\left(1-\frac{d\left(x^{(j)}\oplus\left\{x_{m,i}^{(h,s)}\right\}\right)}{d_m^{(h,s)}}\right)\right) \quad (6)$$
$$\left. then\ x^{(j)}\in X_{m^*}^{o(h,s)}\ else\ x^{(j)}\notin X_{m^*}^{o(h,s)}\right\}.$$

Thus, the feature vector $x^{(j)}$ is assigned to the class from the given alphabet of the corresponding stratum for which the membership function (6) is positive and maximal. Moreover, the decision rules (6), developed within the framework of the geometric approach, enable diagnostic decisions to be made in real time.

4 EXPERIMENTS

This study is dedicated to exploring the application of information-extreme machine learning in ophthalmological diagnostic systems. The training process utilized images of six common ocular pathologies, each representing a corresponding class for recognition purposes [19, 24].

These classes were ordered according to the proposed method of forming a variational series, the visualization of which is presented in Fig. 2. The specified set of images served as a test dataset to evaluate the effectiveness of the developed machine learning approach in the context of computer-aided diagnosis of visual system diseases.

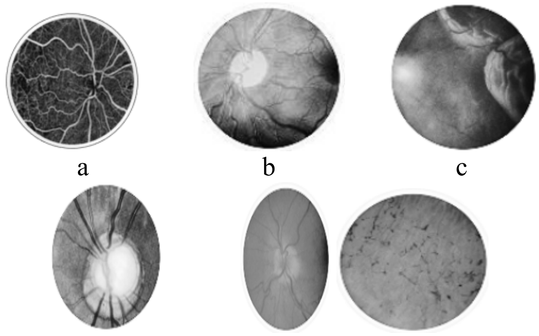

Figure 2 – Photographs of human eye pathologies: a – class X_1^o; b – class X_2^o; c – class X_3^o; d – class X_4^o; e – class X_5^o; f – class X_6^o

Below are the diagnostic classes that form a defined classification system:

1) normal eye condition (recognition class X_1^o);

2) optic nerve atrophy (recognition class X_2^o);

3) retinal detachment (recognition class X_3^o);

4) glaucoma (recognition class X_4^o);

5) optic neuritis (recognition class s X_5^o);

6) pigmentary retinopathy (recognition class X_6^o);

In the process of creating the training dataset for the ODS targeting visual system diseases, image fragments of ocular pathologies with a resolution of 100 × 100 pixels were used. The value of each pixel, expressed as a numerical code ranging from 0 to 255, represented the brightness level of that pixel in the image and served as a diagnostic feature. Assuming invariance of the brightness characteristics, the images were digitized using a Cartesian coordinate system. To enhance the informational content of the input data, the transposed version of the primary training matrix was added to it, effectively doubling the number of diagnostic features. This approach increases the volume of input information and, according to the maximum-distance principle of pattern recognition theory, contributes to an increase in the average interclass distance between the code representations of different image classes [9].

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5 RESULTS

The analysis in works [9, 24] showed that using a hierarchical binary structure for storing diagnostic data in the context of information-extreme machine learning, exemplified by the development of the ODS for eye diseases based on pathology images, was inefficient due to the significant complexity of search, insertion, and deletion operations for diagnostic class elements. Specifically, with the increasing volume of images and their processing, the linear processing of the binary structure leads to a slowdown in processes, negatively affecting the speed of analysis and the accuracy of predictions. Since information-extreme machine learning involves processing large amounts of data for accurate pathology detection, it is advisable to switch to a de-recursive hierarchical structure. This structure will significantly speed up the search and classification processes, thereby enhancing the functional efficiency of eye disease diagnosis and reducing the time required for model training, which, in turn, will provide more accurate and faster results in ophthalmological systems.

To improve the functional efficiency of the ODS, a de-recursive hierarchical structure has been applied (Table 1).

Table 1 – Results of Machine Learning for the ODS

Class	Distance from the Zero Vector	Neighbor Class	Distance to Neighbor Class
X_1^o	15	X_3^o	40
X_2^o	79	X_4^o	30
X_3^o	37	X_5^o	31
X_4^o	59	X_5^o	11
X_5^o	54	X_4^o	11
X_6^o	62	X_4^o	27

The graphical representation of the results presented in Table 1, illustrating the distances from the zero vector and the distances to the neighbor class for each class as points on the plane, is shown in Figure 3.

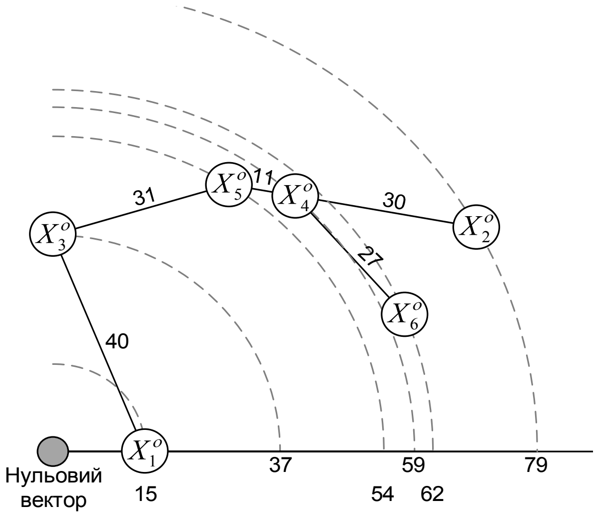

Figure 3 – Graphical Representation of Table 1

According to the information-extreme machine learning scheme using a hierarchical data structure, a binary de-recursive tree was formed, as shown in Figure 4.

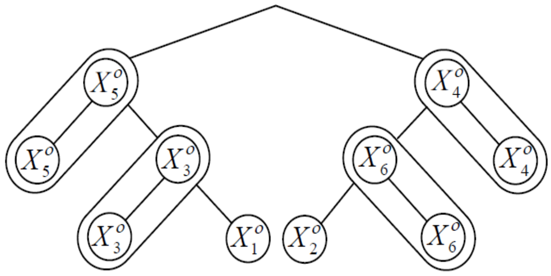

Figure 4 – Three-Level De-Recursive Hierarchical Structure

The analysis of the data presented in Figure 4 indicates the distribution of the alphabet, consisting of six recognition classes, into four final strata. Each of these strata contains two adjacent classes with the highest degree of similarity. In cases where one class belongs to two final strata, the membership function (7) is applied when forming the decision rules described by formula (6). In this case, the optimal geometric parameters of the class are selected, for which the radius, calculated according to procedure (4), takes the minimum value.

For the initial set of recognition classes, a classifier was formed for the first-level classes of the hierarchy $X_0^{o(h=1,s=1)} = X_4^o$ and $X_1^{o(h=1,s=1)} = X_5^o$. During the development, parallel optimization algorithms for the diagnostic class decision (Fig. 5) and optimization of the geometric parameters of decision rules (Fig. 6) were used.

Figure 5 shows the graphical representation of the functional dependence of the averaged information criterion, calculated according to formula (5), on the parameter of the control tolerance field for diagnostic features. This dependence was obtained by applying procedure (3), which involves parallel optimization of the tolerance limits for diagnostic features.

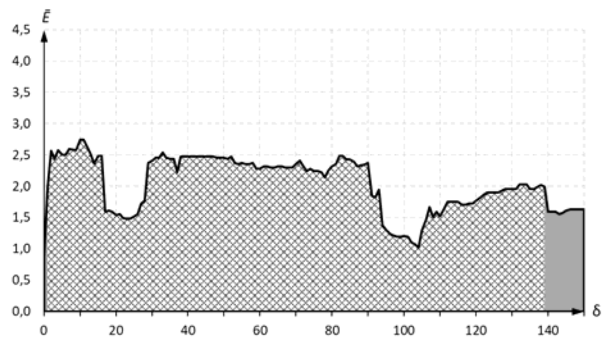

Figure 5 – Graph of the dependence of the information criterion on the parameter of the control tolerance field for the first-level hierarchy

In Figure 5 and subsequent graphical representations, the working domain for the definition of the criterion function (5) is marked by a double dashed line. This

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domain is characterized by values of the first reliability exceeding 0.5 and a second-type error less than 0.5. The analysis of the graph presented in Figure 5 shows that the optimal value of the control tolerance field parameter is $\delta_{1,1}^{*} = 10$ (measured in brightness gradations, which is also used for subsequent measurements). In this case, the maximum value of the information criterion $\overline{E}_{1,1}^{*}$=2.74 is achieved.

The formation of decision rules, described by formula (6), requires the determination of the optimal geometric parameters of the recognition class containers. Figure 6 illustrates the functional dependencies of the information criterion, calculated according to formula (5), on the radii of the hyperspherical containers of the recognition classes.

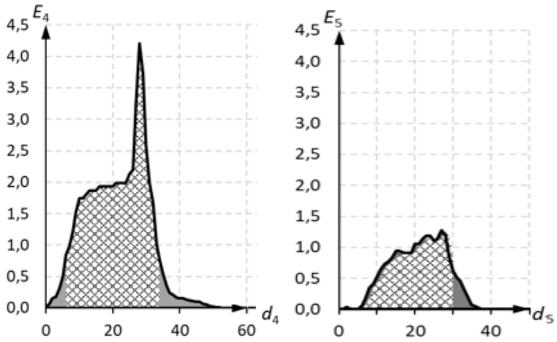

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Figure 6 – Graph of the dependence of the information criterion on the radii of the recognition class containers for the first-level hierarchy: a – class X_4^o; b– class X_5^o

Based on the analysis presented in Figure 6, the optimal radius values for the recognition class containers are: $d_4^* = 28$ (in code units) for recognition class X_4^o and $d_5^* = 27$ for recognition class X_5^o. The maximum values of the Kullback information measure (5) are E_4^*=4.39 and E_5^*=1.27, respectively. The accuracy characteristics, specifically the first reliability and the second-type error for recognition class X_4^o, are as follows: D_{14}=1, β_4 = 0, while for recognition class X_5^o, they are D_{15}=0.97, β_5 = 0.32.

To improve the system's efficiency, two key algorithmic approaches were implemented: sequential optimization of SCT and optimization of the geometric parameters of decision rules. The graphical representation of these methods is shown in Figures 7 and 8, respectively. Figure 7 illustrates the functional dependence of the averaged information criterion, defined by formula (5), on the parameter of the control tolerance field for diagnostic features.

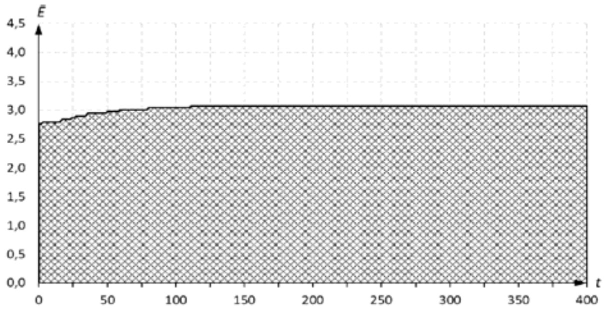

Figure 7 – Graph of the change in the information criterion during the sequential optimization of SCT for the first-level hierarchy

Based on the analysis of Figure 7, the maximum value of the averaged information criterion was reached at the 103rd iteration and amounted to 3.066, which is higher than the value obtained using parallel optimization. Figure 8 demonstrates the results of optimizing the geometric parameters of the recognition class containers obtained during the machine learning process.

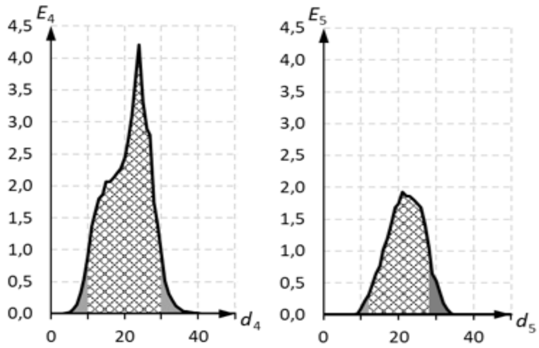

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Figure 8 – Graph of the dependence of the information criterion on the radii of the recognition class containers for the first-level hierarchy: a – class X_4^o; b – class X_5^o

Based on the analysis presented in Figure 8, the optimal radius values for the recognition class containers are: $d_4^* = 24$ for the recognition class X_4^o and $d_5^* = 21$ for the recognition class X_5^o. At the same time, the maximum values of the Kullback information measure (5) are E_4^*=4.39 and E_5^*=1.93, respectively. The accuracy characteristics, specifically the first reliability and the second-type error for recognition class X_4^o, are as follows: D_{14}=1, β_4 =0, while for recognition class X_5^o, they are D_{15}=0.99, β_5 =0.22. A comparison with the previous results shows a significant improvement in these indicators.

For the initial set of recognition classes, a classifier was developed for the second-level classes of the first stratum, X_3^o and X_5^o. In this process, as at the previous level, parallel optimization algorithms for SCT (Fig. 9) and optimization of the geometric parameters of decision rules (Fig. 10) were used.

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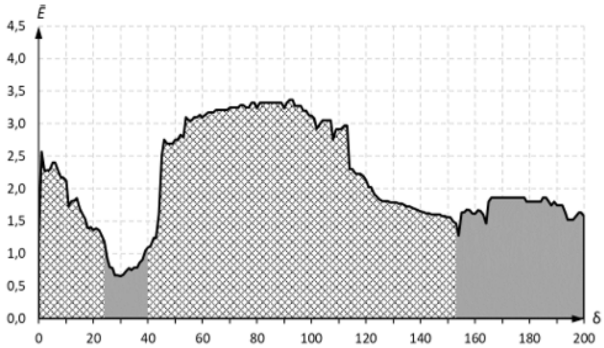

Figure 9 – Graph of the dependence of the information criterion on the parameter of the control tolerance field for the second-level hierarchy of the first stratum

The analysis of the graphical dependency presented in Figure 9 shows the achievement of the maximum value of the averaged Kullback information criterion (5) at the 92nd iteration of the process. The numerical value of this maximum is 3.362. Figure 10 demonstrates the results of optimizing the geometric parameters, obtained through the use of the optimal SCT, which was determined at the previous stage of optimization.

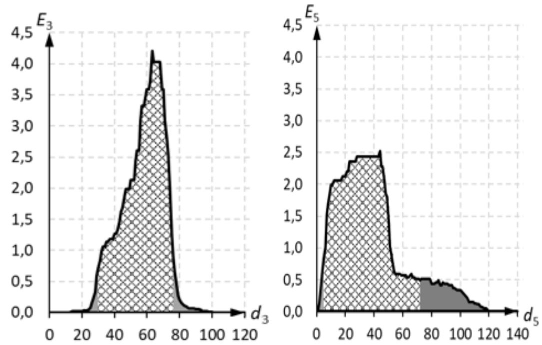

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Figure 10 – Graph of the dependence of the information criterion on the radii of the recognition class containers for the second-level hierarchy of the first stratum: a – class X_3^o; b – class X_5^o

The analysis of Figure 10 shows that the optimal radii of the recognition class containers are: $d_3^* = 63$ for recognition class X_3^o and $d_5^* = 44$ for recognition class X_5^o. The maximum values of the Kullback information measure (5) are E_3^*=4.39 and E_5^*=2.52, respectively. The accuracy characteristics, specifically the first reliability and the second-type error for diagnostic class X_3^o, are as follows: D_{13}=1, β_3=0, while for diagnostic class X_5^o, they are D_{15}=0.86, β_5=0.01.

To improve the system's efficiency, sequential optimization algorithms for SCT (Fig. 11) and optimization of the geometric parameters of decision rules (Fig. 12) were used.

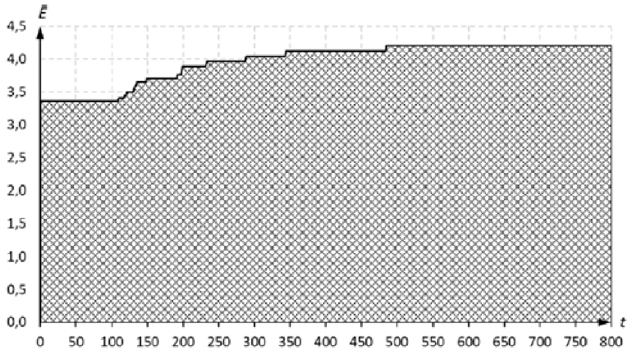

Figure 11 – Graph of the change in the information criterion during the sequential optimization of SCT for the second-level hierarchy of the first stratum

The analysis of the graphical dependence shown in Figure 11 demonstrates that the maximum value of the averaged Kullback information criterion is achieved at the 490th step of the iterative optimization process. The numerical value of this maximum is 4.206. Figure 12 illustrates the results of further optimization of the geometric parameters, carried out using the optimal SCT determined at the previous stage.

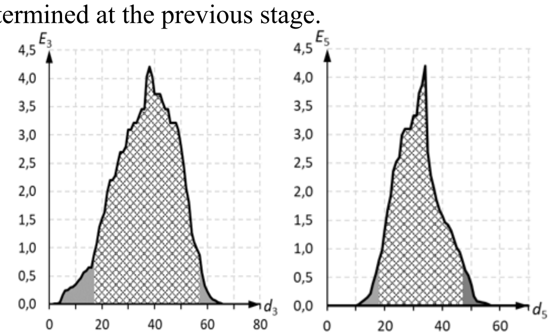

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Figure 12 – Graph of the dependence of the information criterion on the radii of the recognition class containers for the second-level hierarchy of the first stratum: a – class X_3^o; b – class X_5^o

The analysis of Figure 12 shows that the optimal radii of the recognition class containers are: $d_3^* = 38$ for recognition class X_3^o and $d_5^o = 34$ for recognition class X_5^o. At the same time, the maximum values of the Kullback information measure (5) are E_3^*=4.39 and E_5^*=4.39, respectively. The accuracy characteristics, specifically the first reliability and the second-type error for diagnostic class X_3^o, are as follows: D_{13}=1, β_3, while for diagnostic class X_5^o, they are D_{15}=1, β_5=0. A comparison with previous results shows a significant improvement in these indicators.

For the initial diagnostic class alphabet, a classifier was formed for the second-level classes of the second stratum, X_4^o and X_6^o. As in the previous stages of the study, parallel optimization algorithms for SCT (Fig. 12) and optimization of the geometric parameters of decision rules (Fig. 13) were used.

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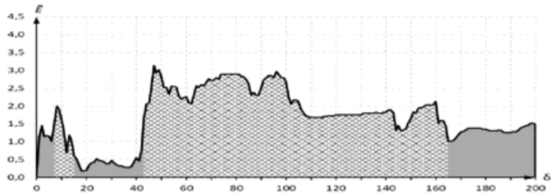

Figure 13 – Graph of the dependence of the information criterion on the parameter of the control tolerance field for the second-level hierarchy of the second stratum

The analysis of the graphical dependency presented in Figure 13 shows that the maximum value of the averaged Kullback information criterion (5) is achieved at the 47th step of the iterative process. The numerical value of this maximum is 3.133. Figure 14 displays the results of optimizing the geometric parameters, obtained through the use of the optimal SCT, determined during the previous optimization stage.

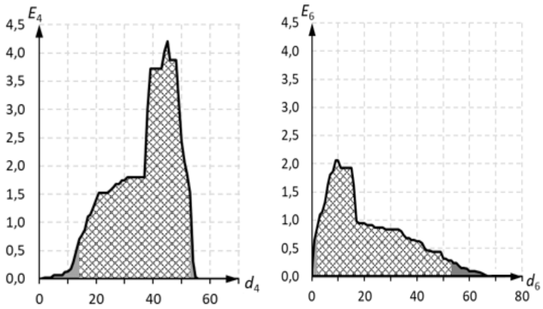

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Figure 14 – Graph of the dependence of the information criterion on the radii of the diagnostic class containers for the second-level hierarchy of the second stratum: a – class X_4^o ; b – class X_6^o

The analysis of Figure 14 shows that the optimal radii of the recognition class containers are: $d_4^* = 45$ for recognition class X_4^o and $d_6^* = 10$ for recognition class X_6^o. The maximum values of the Kullback information measure (5) are E_4^*=4.39 and E_6^*=2.06, respectively. The accuracy characteristics, specifically the first reliability and the second-type error for diagnostic class X_4^o, are as follows: D_{14}=1, β_4=0, while for recognition class X_6^o, they are D_{16}=0.79, β_6=0.0.

To improve the system's efficiency, sequential optimization algorithms for SCT (Fig. 15) and optimization of the geometric parameters of decision rules (Fig. 16) were used.

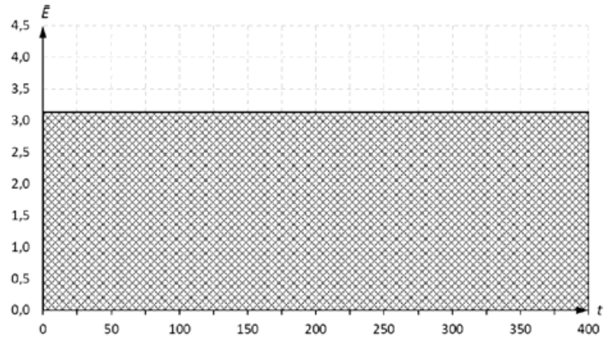

Figure 15 – Graph of the change in the information criterion during the sequential optimization of SCT for the second-level hierarchy of the second stratum

The analysis of the graphical dependency presented in Figure 15 shows that the maximum value of the averaged Kullback information criterion (5) is achieved at the 1st step of the iterative process. The numerical value of this maximum is 3.133. Figure 16 displays the results of optimizing the geometric parameters, obtained through the use of the optimal SCT, determined during the previous optimization stage.

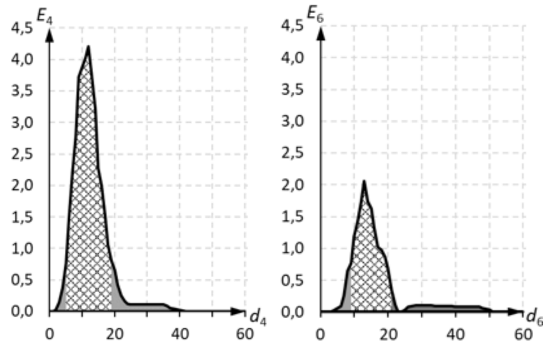

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Figure 16 – Graph of the dependence of the information criterion on the radii of the recognition class containers for the second-level hierarchy of the second stratum: a – class X_4^o ; b – class X_6^o

The analysis of Figure 16 shows that the optimal radii of the recognition class containers are: $d_4^* = 12$ for diagnostic class X_4^o and $d_6^* = 13$ for diagnostic class X_6^o. The maximum values of the Kullback information measure (5) are E_3^*=4.39 and E_5^*=2.06, respectively. The accuracy characteristics, specifically the first reliability and the second-type error for recognition class X_4^o, are as follows: D_{14}=1, β_4=0, while for recognition class X_6^o, they are D_{16}=0.79, β_6=0.

At the next step, a classifier was developed for the third-level classes of the first stratum, X_1^o and X_3^o. As in the previous stages of the study, parallel optimization algorithms for SCT (Fig. 17) were used, as well as algorithms for optimizing the geometric parameters of decision rules (Fig. 18).

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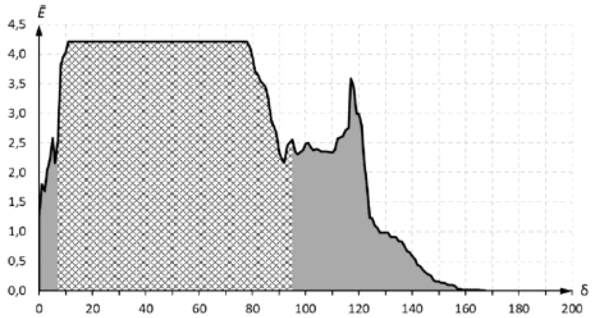

Figure 17 – Graph of the dependence of the information criterion on the parameter of the control tolerance field for the third-level hierarchy of the first stratum

The analysis of the graphical dependency presented in Figure 17 shows that the maximum value of the averaged Kullback information criterion (5) is achieved at the 12th step of the iterative process. The numerical value of this maximum is 4.205.

Figure 18 displays the results of optimizing the geometric parameters, obtained through the use of the optimal SCT, determined during the previous optimization stage.

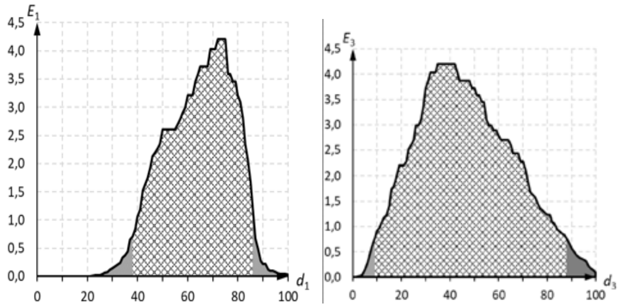

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Figure 18 – Graph of the dependence of the information criterion on the radii of the recognition class containers for the third-level hierarchy of the first stratum: a – class X_1^o ; b – class X_3^o

The analysis of Figure 18 shows that the optimal radii of the recognition class containers are: $d_1^* = 75$ for recognition class X_1^o and $d_3^* = 42$ for recognition class X_3^o. The maximum values of the Kullback information measure (5) are E_1^*=4.39 and E_3^*=4.39, respectively. The accuracy characteristics, specifically the first reliability and the second-type error for recognition class X_1^o, are as follows: D_{11}=1, β_1=0, while for recognition class X_3^o, they are D_{13}=1, β_3=0. Since an error-free classifier has been built, the use of sequential optimization algorithms for SCT for the first stratum classes of the third-level hierarchy is unnecessary.

At the next step, a classifier was developed for the third-level classes of the second stratum, X_2^o and X_6^o. As in the previous stages, parallel optimization algorithms for SCT (Fig. 19) were used, as well as algorithms for optimizing the geometric parameters of decision rules (Fig. 20) in the classification process.

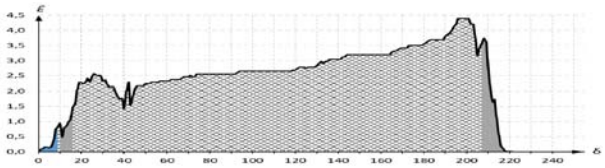

Figure 19 – Graph of the dependence of the information criterion on the parameter of the control tolerance field for the third-level hierarchy of the second stratum

The analysis of the graphical dependency presented in Figure 19 shows that the maximum value of the averaged Kullback information criterion (5) is achieved at the 192nd step of the iterative process. The numerical value of this maximum is 4.478. Figure 20 displays the results of optimizing the geometric parameters, obtained through the use of the optimal SCT, determined during the previous optimization stage.

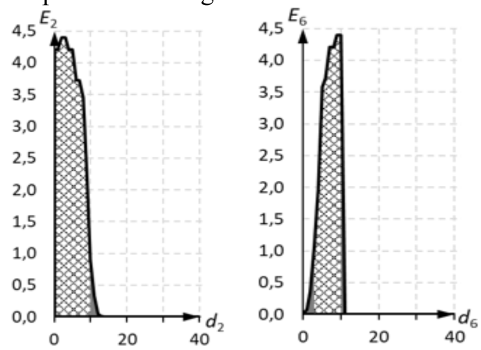

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Figure 20 – Graph of the dependence of the information criterion on the radii of the recognition class containers for the third-level hierarchy of the second stratum: a – class X_2^o ; b – class X_6^o

The analysis of Figure 20 shows that the optimal radii of the recognition class containers are: $d_2^* = 3$ for recognition class X_2^o and $d_3^* = 10$ for recognition class X_6^o. The maximum values of the Kullback information measure (5) are E_2^*=4.39 and E_3^*=4.39, respectively. The accuracy characteristics, specifically the first reliability and the second-type error for recognition class X_2^o, are as follows: D_{12}=1, β_2=0, while for recognition class X_6^o, they are D_{16}=1, β_6=0. Since an error-free classifier has been built for the first stratum classes of the third-level hierarchy, the use of sequential optimization algorithms for SCT is also unnecessary.

Thus, the comparative analysis of the training results of the computerized ODS, which uses binary and de-recursive hierarchical structures of decision rules, confirms the high effectiveness of these approaches in the task of classifying six functional states of the human eye based on images. Both structures demonstrate the ability to ensure the accurate formation of a classifier that eliminates errors during the processing of the training matrix.

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6 DISCUSSION

The results of information-extremal machine learning based on a hierarchical data structure in the form of a recursive tree open new possibilities for solving the problem of enhancing the functional efficiency of the ODS. Using the example of information synthesis in the eye disease diagnosis system based on the characteristic signs of pathologies, the possibility of forming highly accurate diagnostic rules in the form of a three-layer recursive tree is demonstrated. Unlike a linear rule structure in a fixed diagnostic feature space, this method operates with optimal tolerance systems for each diagnostic class. Each layer of the tree uses strata consisting of pairs of nearest neighbor classes. The formation of decision rules is carried out using information-extremal machine learning methods with a depth of two levels for each such pair. It was established that, at the first level, it is advisable to apply the standard iterative optimization procedure for genotype parameters, while at the second level, a parallel-sequential optimization of phenotype functional parameters is applied, specifically the control tolerances for diagnostic features. This improves both the recognition accuracy and the efficiency of the machine learning process.

CONCLUSIONS

An important task of information analysis and synthesis of the intellectual component of the ODS, capable of information-extreme machine learning, is solved.

The scientific novelty of the obtained results lies in the fact that, for the first time, a methodology for selecting the training sample has been proposed. It determines the weighting coefficients that characterize the term and utility of the function for a given initial set of precedents and a specified division of the function space. It characterizes the individual absolute and relative informativeness of instances relative to the centers and boundaries of feature intervals based on the weighting values. This allows automating the sample analysis and its division into subsets, which, in turn, reduces the dimensionality of the training data. This, in turn, shortens the time and ensures acceptable accuracy for training the neural model.

The practical significance of the obtained results lies in the fact that software has been developed to implement the proposed indicators, and experiments have been conducted to study their properties. The results of the experiment allow recommending the proposed indicators for practical use, as well as determining the effective conditions for applying the proposed indicators.

Prospects for further research lie in studying the proposed set of indicators for a wide range of practical tasks.

REFERENCES

1. Lírio L. R. de, Malheiros É. F. R., Stabile G. et al. Retinoblastoma e a radiologia intervencionista: papel no tratamento da população infantil, *Brazilian Journal of Implantology and Health Sciences*, 2024, Vol. 8, № 6, pp. 3380–3399. DOI: 10.36557/2674-8169.2024v6n8p3380-3399.
2. Stitt A. W., Lois N., Medina R. J. et al. Advances in Our Understanding of Diabetic Retinopathy, *Clin Sci (Lond)*, 2013, Vol. 125, №1, pp. 1–17. DOI: 10.1042/CS20120588.
3. Cho N. H., Shaw J. E., Karuranga S. et al. IDF Diabetes Atlas: Global Estimates of Diabetes Prevalence for 2017 and Projections for 2045, *Diabetes Research and Clinical Practice*, 2018, Vol. 138, pp. 271–281. DOI: 10.1016/j.diabres.2018.02.023.
4. Oshika T. Artificial Intelligence Applications in Ophthalmology, *JMAJ*, 2025, Vol. 8, № 1, pp. 66–75. DOI: 10.31662/jmaj.2024-0139.
5. Li Z., Wang L., Wu X. et al. Artificial Intelligence in Ophthalmology: The Path to the Real-World Clinic, *Cell Reports Medicine*, 2023, Vol. 4, № 7, Article number: 101095. DOI: 10.1016/j.xcrm.2023.101095.
6. Srivastava O., Tennant M., Grewal P. et al. Artificial Intelligence and Machine Learning in Ophthalmology: A Review, *Indian Journal of Ophthalmology*, 2023, Vol. 71, №1, pp. 11–17. DOI: 10.4103/ijo.IJO_1569_22.
7. Shelehov I. V., Prylepa D. V., Khibovska Y. O. et al. Machine learning decision support systems for adaptation of educational content to the labor market requirements, *Radio Electronics, Computer Science, Control*, 2023, Vol. 1, pp. 62–72. DOI: 10.15588/1607-3274-2023-1-6.
8. Prylepa D.V. Informatsiyno-ekstremal'na intelektual'na tekhnolohiya diahnostuvannya emotsiyno-psykhichnoho stanu lyudyny. Dys. c.t.n. [Information-extreme intellectual technology for diagnosing the emotional and mental state of a person. Candidate of Technical Sciences diss.]. Kharkiv, 2024. 188 p.
9. Shelehov I. V., Barchenko N. L., Prylepa D. V. et al. Information-extreme machine training system of functional diagnosis system with hierarchical data structure, *Radio Electronics, Computer Science, Control*, 2022, Vol. 2, pp. 189–200. DOI: 10.15588/1607-3274-2022-18.
10. Chandra A., Romano M. R., Chao D. L. Implementing the New Normal in Ophthalmology Care Beyond COVID-19, *European Journal of Ophthalmology*, 2020, Vol. 31, № 2. DOI: 10.1177/1120672120975331.
11. Bejnordi B. E., Zuidhof G., Balkenhol M. et al. Context-Aware Stacked Convolutional Neural Networks for Classification of Breast Carcinomas in Whole-Slide Histopathology Images, *Journal of Medical Imaging*, 2017, Vol. 4, № 4, pp. 1. DOI: 10.1117/1.jmi.4.4.044504.
12. Gu H., Gu Y., Wei A. et al. Deep Learning for Identifying Corneal Diseases from Ocular Surface Slit-Lamp Photographs, *Scientific Reports*, 2020, Vol. 10, Article number: 17851. DOI: 10.1038/s41598-020-75027-3.
13. Kermany D. S., Goldbaum M., Cai W. et al. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning, *Cell*, 2018, Vol. 172, №5, pp. 1122–1131.e9. DOI: 10.1016/j.cell.2018.02.010.
14. Gulshan V., Peng L., Coram M. et al. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs, *JAMA*, 2016, Vol. 316, №22, pp. 2402–2410. DOI: 10.1001/jama.2016.17216.
15. Woreta F. A., Gordon L. K., Pérez-González C. E. Enhancing Diversity in the Ophthalmology Workforce, *Ophthalmology*, 2022, Vol. 129, №10, pp. 127–136. DOI: 10.1016/j.ophtha.2022.06.033.
16. Lu W., Tong Y., Yu Y. et al. Applications of Artificial Intelligence in Ophthalmology: General Overview, *Journal of Ophthalmology*, 2018, Article number: 30581604, pp. 1–15. DOI: 10.1155/2018/5278196.

DOI 10.15588/1607-3274-2025-3-11

17. Classification and Diagnosis of Diabetes: Standards of Medical Care in Diabetes-2019, *Diabetes Care*, 2019, Vol. 42(Supplement 1), pp. 13–28. DOI: 10.2337/dc19-s002.
18. Kermany D. S., Goldbaum M., Cai W. et al. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning, *Cell*, 2018, Vol. 172, №5, pp. 1122–1131.e9. DOI: 10.1016/j.cell.2018.02.010.
19. Putivets', A.V. Intelektual'na systema vyyavlennya urazhen' sitkivky oka: robota na zdobuttya kvalifikatsiynoho stupenya bakalavra; spets.: 122 – komp"yuterni nauky (informatyka) [Elektron. resurs] / A.V. Putivets'; nauk. kerivnyk I.V. Shelekhov. – Sumy: SumDU, 2020. – 72 s. – Rezhym dostupu: http://essuir.sumdu.edu.ua:8080/handle/123456789/79779.
20. Suprunenko M. K., Zborshchyk O. P., Sokolov O. Information-extreme machine learning of wrist prosthesis control system based on the sparse training matrix, *Journal of Engineering Sciences*, 2022, Vol. 9, iss. 2, pp. 28–35. DOI: 10.21272/jes.2022.9(2).e4.
21. Dovbysh A., Zimovets V. Hierarchical Algorithm of the Machine Learning for the System of Functional Diagnostics of the Electric Drive, *Advanced Information Systems and Technologies, VI International Conference*, *Sumy, 16–18 May 2018*: *proceedings*, Sumy, Sumy State University, 2018, pp. 85–88.
22. Moskalenko V. V., Moskalenko A. S., Korobov A. G. Models and methods of intellectual information technology of autonomous navigation for compact drones, *Radio Electronics, Computer Science, Control*, 2018, № 3, pp. 68–77. DOI: 10.15588/1607-3274-2018-3-8.
23. Dovbysh A., Shelehov I., Romaniuk A., et al. Decision-making support system for diagnosis of oncopathologies by histological images, *Journal of Pathology Informatics*, 2023, Article number: 100193. DOI: 10.1016/j.jpi.2023.100193.
24. Shelehov I., Prylepa D., Khibovska Y. et al. Information-Extreme Machine Learning of an Ophthalmic Diagnostic System with a Hierarchical Class Structure, *Artificial Intelligence*, 2024, № 3, pp. 114–125. DOI: 10.15407/jai2024.03.114.

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ІЄРАРХІЧНЕ МАШИННЕ НАВЧАННЯ СИСТЕМИ ФУНКЦІОНАЛЬНОГО ДІАГНОСТУВАННЯ ПАТОЛОГІЙ ОКА НА ОСНОВІ ІНФОРМАЦІЙНО-ЕКСТРЕМАЛЬНОГО ПІДХОДУ

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АНОТАЦІЯ

Актуальність. Розглянуто задачу інформаційно-екстремального машинного навчання системи діагностування патологій ока за характерними ознаками захворювань. Об'єктом дослідження є процес ієрархічного машинного навчання системи діагностування офтальмологічних захворювань. Старіння населення та поширення захворювань очей, таких як глаукома, атрофія зорового нерва, відшарування сітківки та діабетична ретинопатія, вимагають ефективних методів ранньої діагностики для запобігання втрати зору. Традиційні методи діагностики значною мірою залежать від досвіду лікаря, що може призводити до помилок. Використання штучного інтелекту (ШІ) та машинного навчання (МН) може суттєво покращити точність і швидкість діагностування, що робить цю тему надзвичайно актуальною.

Мета. Підвищення функціональної ефективності комп'ютеризованої системи діагностування патологій ока на основі зображень.

Метод. Запропоновано метод інформаційно-екстремального ієрархічного машинного навчання для системи діагностування патологій ока на основі характерних ознак захворювань. Метод базується на функціональному підході до моделювання когнітивних процесів природного інтелекту, що забезпечує адаптивність системи діагностування за будь-яких початкових умов формування зображень патологій і дозволяє гнучко перенавчати систему при збільшення потужності алфавіту класів розпізнавання. Основою методу є принцип максимізації критерію функціональної ефективності на базі модифікованої інформаційної міри Кульбака, яка є функціоналом від точносних харатеристик діагростичних правил. Процес навчання розглядається як ітераційна процедура оптимізації параметрів роботи системи діагностування за цим інформаційним критерієм. На основі запропонованої категорійної функціональної моделі розроблено алгоритм інформаційно-екстремального машинного навчання з ієрархічною структурою даних у вигляді бінарного декурсивного дерева. Така структура даних дозволяє розділяти велику кількість класів розпізнавання на пари найближчих сусідів, для яких параметри машинного навчання оптимізуються за лінійним алгоритмом необхідної глибини.

Результати. Розроблено інтелектуальну технологію діагностики патологій ока, яка включає комплекс інформаційного, алгоритмічного та програмного забезпечення. Проведено порівняльний аналіз ефективності різних методів організації вирішальних правил у процесі навчання системи. Виявлено, що використання декурсивних ієрархічних структур класифікаторів дозволяє досягти вищої точності діагностики у порівнянні з бінарними класифікаторами.

Висновки. Розроблена інтелектуальна система комп'ютерного діагностування патологій ока демонструє високу ефективність та точність. Впровадження такої системи у медичну практику може суттєво підвищити якість діагностики очних захворювань, знизити навантаження на лікарів та мінімізувати ризик помилкових діагнозів. Подальші дослідження можуть бути спрямовані на вдосконалення алгоритмів та розширення їх застосування на інші типи медичних зображень.

КЛЮЧОВІ СЛОВА: комп'ютерна діагностика патології ока, штучний інтелект, машинне навчання, обробка зображень, розпізнавання образів, інформаційно-екстремальна технологія, ієрархічна структура класифікаторів.

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ЛІТЕРАТУРА

1. Lírio L. R. de. Retinoblastoma and interventional radiology: role in the treatment of children / [L. R. de Lírio, É. F. R. Malheiros, G. Stabile, L. C. V. et al.] // Brazilian Journal of Implantology and Health Sciences. – 2024. – №8(6). – P. 3380–3399. DOI:10.36557/2674-8169.2024v6n8p3380-3399.
2. Advances in Our Understanding of Diabetic Retinopathy / [A. W. Stitt, N. Lois, R. J. Medina et al.] // Clin Sci (Lond). – 2013. – Vol. 125(1). – P. 1–17. DOI: 10.1042/CS20120588.
3. IDF Diabetes Atlas: Global Estimates of Diabetes Prevalence for 2017 and Projections for 2045 / [N. H. Cho, J. E. Shaw, S. Karuranga et al.] // Diabetes Research and Clinical Practice. – 2018. – Vol. 138. – P. 271–281. DOI: 10.1016/j.diabres.2018.02.023.
4. Oshika T. Artificial Intelligence Applications in Ophthalmology / T. Oshika // JMAJ. – 2025. – №8(1). – P. 66–75. DOI: 10.31662/jmaj.2024-0139.
5. Artificial Intelligence in Ophthalmology: The Path to the Real-World Clinic / [Z. Li, L. Wang, X. Wu et al.] // Cell Reports Medicine. – 2023. – Vol. 4, Issue 7, Article number: 101095. DOI: 10.1016/j.xcrm.2023.101095.
6. Artificial Intelligence and Machine Learning in Ophthalmology: A Review / [O. Srivastava, M. Tennant, P. Grewal et al.] // Indian Journal of Ophthalmology. – 2023. – Vol. 71(1). – P. 11–17. DOI: 10.4103/ijo.IJO_1569_22.
7. Machine Learning Decision Support Systems for Adaptation of Educational Content to the Labor Market Requirements / [I. V. Shelehov, D. V. Prylepa, Y. O. Khibovska et al.] // Radio Electronics, Computer Science, Control. – 2023. – Vol. 1. – P. 62–72. DOI: 10.15588/1607-3274-2023-1-6.
8. Прилепа Д. В. Інформаційно-екстремальна інтелектуальна технологія діагностування емоційно-психічного стану людини : дис. … канд. техн. наук : 05.13.06 / Прилепа Дмитро Вікторович. – Харків, 2024. 188 с.
9. Information-extreme machine training system of functional diagnosis system with hierarchical data structure / [I. V. Shelehov, N. L. Barchenko, D. V. Prylepa et al.] // Radio Electronics, Computer Science, Control. – 2022. – №2. – P. 189–200. DOI:10.15588/1607-3274-2022-18.
10. Chandra A. Implementing the New Normal in Ophthalmology Care Beyond COVID-19 / A. Chandra, M. R. Romano, D. L. Chao // European Journal of Ophthalmology. – 2020. – Vol. 31, Issue 2. – DOI: 10.1177/1120672120975331.
11. Bejnordi B. E. Context-Aware Stacked Convolutional Neural Networks for Classification of Breast Carcinomas in Whole-Slide Histopathology Images / [B. E. Bejnordi, G. Zuidhof, M. Balkenhol et al.] // Journal of Medical Imaging. – 2017. – Vol. 4(4). – P. 1. DOI: 10.1117/1.jmi.4.4.044504.
12. Deep Learning for Identifying Corneal Diseases from Ocular Surface Slit-Lamp Photographs / [H. Gu, Y. Gu, A. Wei et al.] // Scientific Reports. – 2020. – Vol. 10, Article number: 17851. DOI: 10.1038/s41598-020-75027-3.
13. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning / [D. S. Kermany, M. Goldbaum, W. Cai et al.] // Cell. – 2018. – Vol. 172(5). – P. 1122–1131.e9. DOI: 10.1016/j.cell.2018.02.010.
14. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs / [V. Gulshan, L. Peng, M. Coram et al.] // JAMA. – 2016. – Vol. 316(22). – P. 2402–2410. DOI: 10.1001/jama.2016.17216.
15. Woreta F. A. Enhancing Diversity in the Ophthalmology Workforce / F. A. Woreta, L. K. Gordon, C. E. Pérez-González // Ophthalmology. – 2022. – Vol. 129(10). – P. 127–136. DOI: 10.1016/j.ophtha.2022.06.033.
16. Applications of Artificial Intelligence in Ophthalmology: General Overview / [W. Lu, Y. Tong, Y. Yu et al.] // Journal of Ophthalmology. – 2018. – P. 1–15. DOI: 10.1155/2018/5278196.
17. Classification and Diagnosis of Diabetes: Standards of Medical Care in Diabetes-2019 / American Diabetes Association // Diabetes Care. – 2018. – Vol. 42(Supplement 1). – P. S13–S28. DOI: 10.2337/dc19-s002.
18. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning / [D. S. Kermany, M. Goldbaum, W. Cai et al.] // Cell. – 2018. – Vol. 172(5). – P. 1122–1131.e9. DOI: 10.1016/j.cell.2018.02.010.
19. Путівець А.В. Інтелектуальна система виявлення уражень сітківки ока: робота на здобуття кваліфікаційного ступеня бакалавра; спец.: 122 – комп’ютерні науки (інформатика) [Електрон. ресурс] / А. В. Путівець; наук. керівник І. В. Шелехов. – Суми: СумДУ, 2020. – 72 с. – Режим доступу: http://essuir.sumdu.edu.ua:8080/handle/123456789/79779.
20. Suprunenko M. K. Information-extreme machine learning of wrist prosthesis control system based on the sparse training matrix / M. K. Suprunenko, O. P. Zborshchyk, O. Sokolov // Journal of Engineering Sciences. – 2022. – Vol. 9, Issue 2. – P. 28–35. – DOI: 10.21272/jes.2022.9(2).e4.
21. Dovbysh A. Hierarchical Algorithm of the Machine Learning for the System of Functional Diagnostics of the Electric Drive / A. Dovbysh, V. Zimovets // Advanced Information Systems and Technologies : VI International Conference, Sumy, 16–18 May 2018 : proceedings. – Sumy: Sumy State University, 2018. – P. 85–88.
22. Moskalenko V. V. Models and methods of intellectual information technology of autonomous navigation for compact drones / V. V. Moskalenko, A. S. Moskalenko, A. G. Korobov // Radio Electronics, Computer Science, Control. – 2018. – № 3. – P. 8. – DOI: 10.15588/1607-3274-2018-3-8.
23. Dovbysh A. Decision-making support system for diagnosis of oncopathologies by histological images / [A. Dovbysh, I. Shelehov, A. Romaniuk et al.] // Journal of Pathology Informatics. – 2023. – P. 100193. – DOI: 10.1016/j.jpi.2023.100193.
24. Shelehov I. Information-Extreme Machine Learning of an Ophthalmic Diagnostic System with a Hierarchical Class Structure / I. Shelehov, D. Prylepa, Y. Khibovska // Artificial Intelligence. – 2024. – №3. – P. 114–125. DOI: 10.15407/jai2024.03.114.

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