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DEEP INFORMATION-EXTREME MACHINE LEARNING FOR AUTONOMOUS UAV BASED ON DECURSIVE DATA STRUCTURE FOR SEMANTIC SEGMENTATION OF DIGITAL IMAGE OF A REGION

***The subject of the research** is functional categorical models of deep information-extreme machine learning based on linear and hierarchical data structures, methods for optimizing machine learning parameters based on information criteria and constructing a decursive binary data tree for a given alphabet of recognition classes. **The aim of the research** is to improve the accuracy of machine learning for an autonomous UAV for semantic segmentation of a digital image of a region obtained via an optoelectronic observation channel. This goal is achieved by developing a method of deep information-extreme machine learning for an on-board recognition system of an autonomous UAV using a decursive binary data structure. **A new method** of deep information-extreme machine learning for autonomous UAVs has been developed, based on a hierarchical data structure in the form of a decursive binary tree. The novelty of the method lies in the maximization of the average interclass code distance within a given dimensionality of the Hamming feature space by optimizing the selection level of coordinates of statistically averaged binary realizations of the recognition classes. At the same time, the level of depth of information-extreme machine learning according to the principle of deferred decisions is determined by the number of parameters of the system's functioning that are optimized according to the information criterion. This approach, unlike neural-like structures, provides flexibility for the onboard recognition system during retraining in the event of an expansion of the recognition class alphabet. The Kullback-Leibler information measure modified by the authors serves as a criterion for optimizing machine learning parameters. In addition, the proposed method involves the transformation of the input training matrix into a working binary matrix specified in the Hamming space, which in the process of machine learning adapts to its maximum accuracy. **Results:** Based on the results of deep information-extreme machine learning, error-free decision rules based on the training matrix were constructed within the framework of a geometric approach. It is shown that the accuracy of the deep information-extreme machine learning is affected by the sequence of optimization of the parameters of the recognition system. The results of functional testing and cross-validation have confirmed the high accuracy of information-extreme machine learning for an autonomous UAV, as demonstrated by semantic segmentation of a digital image of a region. **Conclusions:** For the first time, a method of deep information-extreme machine learning based on a hierarchical data structure in the form of a decursive binary tree has been developed, which, unlike the known ones, additionally optimizes the level of selection for coordinates of binary averaged vectors of recognition features.*

***Keywords:** information-extreme machine learning; information criterion; optimization; autonomous UAV; decursive binary tree; digital image of the region.*

1. Introduction

1.1. Motivation

Providing a UAV with autonomy allows expanding its functionality, increasing the probability of mission completion, and reducing the burden on the personnel of the ground control station. There are known examples of the use of autonomous UAVs in the agricultural sector [1, 2], for monitoring nuclear power plants [3], and ecosystems [4, 5], recognition of ground objects [6, 7], military [8], etc. One of the areas of application of autonomous UAVs is mapping the observation region [9, 10] which has practical significance for various sectors of the socio-economic sphere of society. An analysis of the current state of development of autonomous UAVs for observing the Earth's surface showed that the main direction of their improvement is the application of intelligent information technologies based on machine learning. In paper [10], the application of a local descriptor for semantic segmentation in combination with machine learning is considered. In this case, there is an unresolved issue of the choice of brightness threshold for detecting a ground object. At the same time, the issue of developing a highly accurate and operational machine learning method for the onboard system of an autonomous UAV for semantic segmentation of a digital image of the observation region is acute. A promising direction for solving this issue is the development of machine learning methods within the framework of a functional approach to modeling cognitive processes of natural intelligence [11]. Therefore, the development of a machine learning method that models the mechanism of natural intelligence in constructing and making classification decisions is an urgent task.

1.2. State of the Art

Increasing the functional efficiency of an autonomous UAV depends mainly on the availability of a relevant input mathematical description and a machine learning method with high accuracy and efficiency in making classification decisions. The paper [12] emphasizes the feasibility of constructing decision rules obtained in the process of machine learning within the framework of a geometric approach, which allows ensuring their practical invariance to the multidimensionality of the recognition feature dictionary. Known methods of information synthesis of intelligent UAVs for recognizing terrestrial natural and infrastructure objects, including the use of artificial neural networks [7, 13], do not fully meet the practical requirements due to complications of a scientific and methodological nature. Such complications are mainly due to arbitrary initial conditions for image formation, the intersection of recognition classes in the feature space, and the multidimensionality of the feature dictionary and the alphabet of recognition classes. The most common methods of information synthesis for intelligent UAVs in recognizing natural and infrastructural ground objects utilize artificial neural networks [14, 15]. In [16], an autonomous navigation system for UAV based on deep learning CNNs is proposed, which enables the recognition of navigational obstacles. The system under consideration is multisensory, allowing it to perceive the entire environment around the drone for obstacle detection and avoidance, path planning, and movement in all directions. Study [17] presents a monitoring system for the development of citrus crops in precision agriculture. For semantic pixel-wise segmentation of citrus leaves to detect phytodiseases, a CNN with the Visual Geometry Group 16 (VGG16) architecture was used.

The main drawbacks of applying CNNs for semantic segmentation are their sensitivity to the high dimensionality of the feature recognition space and fundamental complications in retraining the system due to the increased complexity of the recognition class alphabet. Additionally, using CNNs requires a large training dataset, which leads to increased time and material costs of machine learning for autonomous UAVs. These complications are mainly caused by arbitrary initial conditions in image formation, overlapping recognition classes in the feature space, and the high dimensionality of the feature dictionary and recognition class alphabet.

In study [18], the robustness and accuracy of an image segmentation method based on the ant colony optimization algorithm are investigated under varying levels of additive Gaussian noise, along with a comparison of its performance against the classical segmentation approach using the Sobel filter. The proposed method has practical value for determining the contour of terrain areas during pixel-wise semantic segmentation of digital images of the monitored region.

Overall, the complexities of modern intelligent data analysis technologies, including neural-like structures, are mainly caused by arbitrary initial conditions in image formation, overlapping recognition classes in the feature space, and the high dimensionality of the feature dictionary and recognition class alphabet.

One of the promising areas of information synthesis of the onboard autonomous UAV system for semantic segmentation is the application of ideas and methods of information-extreme intellectual technology (IEI technology) for data analysis, developed within the framework of a functional approach to modeling cognitive processes of natural intelligence [19, 20]. The data mining methods proposed within this technology are based on maximizing the information capacity of the system during the machine learning process. Contrary to neural-like structures, the adaptation of the input mathematical description in IEI technology methods is carried out by optimizing machine learning parameters according to the information criterion. Study [21] examines information-extreme machine learning with the third level of depth for semantic segmentation of a digital image of a region, where the input data had a linear structure. Information-extreme machine learning for UAVs based on a hierarchical data structure was explored in study [22]. As a result, the multiclass machine learning problem was reduced to a binary classification task for each stratum of a decursive binary tree, which enabled the construction of highly reliable decision rules by implementing the basic second-level machine learning algorithm. However, in cases of significant overlap between recognition classes in the feature space, the accuracy of information-extreme machine learning heavily depends on its depth level. Therefore, despite successful applications of

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information-extreme machine learning, further research is needed to ensure high accuracy as the size of the recognition class alphabet increases.

1.3. Objectives and approaches

The aim of the article is to improve the accuracy of information-extreme machine learning for an autonomous UAV for semantic segmentation of a digital image of a region by developing a method of deep information-extreme machine learning for an autonomous UAV based on a decursive binary data structure. The developed algorithm must be suitable for use by intelligent reconnaissance UAVs with the 2nd level of autonomy for recognizing natural and infrastructural ground objects. Within the framework of the functional approach, to build highly reliable decision rules, the method must adapt the input mathematical description for increasing the accuracy of machine learning. Similar to natural intelligence, such adaptation is achieved by optimizing the system's operational parameters in accordance with the information criterion. In this case, according to the principle of deferred decisions, the required level of machine learning depth is determined by the number of optimization parameters. At the same time, decision rules constructed using the optimal geometric parameters of radial basis containers for recognition classes in the information-theoretic sense demonstrate practical invariance to the dimensionality of the feature space. In addition, decision rules built within the framework of the geometric approach are characterized by high efficiency in making classification decisions due to the minimal complexity of calculations.

The structure of the article includes several main sections. Section 2 presents the formalized statement for the problem of information synthesis during the training of an autonomous on-board system. Two different algorithms of machine learning were described for linear and hierarchical data structures. Section 3 presents the results of experimental testing of the proposed UAV identification model and training method. A detailed discussion of the research results is provided in Section 4. The concluding section 5 formulates the main conclusions and outlines directions for further research.

2. Materials and methods of research

2.1. Formalized statement of the research problem

Let's consider, within the framework of IEI technology, a formalized formulation of the problem of information synthesis in a learnable on-board system of an autonomous UAV for the semantic segmentation of a digital image of the region. Let's assume that we are given an alphabet of recognition classes $\{X_m^o \mid m = \overline{1,M}\}$, that characterize different natural areas of the observation region in the image. Accordingly, a training matrix of the type "object property" $\| y_{m,i}^{(j)} \|, i = \overline{1,N}, j = \overline{1,n}$, is formed, where N is the number of recognition features; n is the number of structured feature vectors (hereinafter simply referred to as vectors) of the recognition classes, respectively.

According to the concept of IEI technology, the input training matrix is transformed into a working binary matrix specified in the Hamming space, which, through permissible transformations in the process of machine learning, is adapted to its maximum accuracy. Therefore, in the Hamming space, it is necessary to specify a structured vector of optimization parameters (hereinafter in the text in the information sense), the number of which determines the level of machine learning depth. For example, for machine learning for an autonomous UAV to recognize class X_m^o vectors, such a vector will be represented in the form of a structure

$$g_m = < d_m; \delta; \{\delta_i \mid i = \overline{1,N}\}; \rho >, \qquad (1)$$

where d_m is the radius of the hyperspherical container of the recognition class X_m^o , which is reconstructed in the radial basis of the recognition feature space; δ is a parameter equal to half of the symmetric field of control tolerances for recognition features; δ_i is a parameter of the control tolerance field for the i-th recognition feature; ρ is the level of selection of coordinates of binary averaged feature vectors that determine the geometric centers of hyperspherical containers of recognition classes in the feature space.

The range of values of the radius of the container of the recognition class X_m^o is given by the inequality $d_m < d(x_m \oplus x_c)$, where $d(x_m \oplus x_c)$ is an inter-center code distance between the nearest neighboring recognition classes X_m^o and X_c^o, which is defined as the code distance between the averaged recognition feature vectors $x_m \in X_m^o$ and $x_c \in X_c^o$.

The range of values of parameters δ and δ_i is given by the interval $[0; \delta_H / 2]$, where δ_H is a width for range of values for the normalized control tolerance field. The range of values for selection level ρ is an interval $[0; 1]$.

In the machine learning process of autonomous UAV it is necessary to:

1) Determine the optimal values of machine learning parameters (1) that provide the maximum average value of the information criterion over the alphabet of recognition classes

$$\overline{E}^* = \frac{1}{M}\sum_{m=1}^{M} \max_{G_E \cap G_d} E_m(d), \qquad (2)$$

where $E_m(d)$ is an information criterion for optimizing machine learning parameters, which is calculated at the current radius d of the recognition class container X_m^o; G_E is a working (permissible) area of definition of the information criterion function of optimization; G_d is the permissible range of values of the radiuses of the recognition class container, which is reconstructed in the radial basis of the binary Hamming feature space;

2) Using the optimal geometric parameters of the recognition class containers obtained during the machine learning process, construct decision rules that are error-free according to the training matrix;

3) At the functional testing stage, check the accuracy of machine learning according to the constructed decision rules.

Thus, the information synthesis of a learning onboard recognition system for an autonomous UAV is carried out by optimizing the operating parameters (1) according to the information criterion (2) in the process of information-extreme machine learning.

2.2. Machine learning on linear data structure

Within the framework of the functional approach to modeling cognitive processes, the functional categorical model of information-extreme machine learning is constructed in the form of a directed graph. At the same time, the input mathematical description of the functional categorical model of machine learning is presented in the form of a structure

$$I_{ent} = < F, T, \Omega, K, Z; Y^{|M|}, X^{|M|}; f_1, f_2. >,$$

where F is the space of factors that affect the image; T is a set of moments in time of receiving information; Ω is a recognition feature space; Z is an alphabet of recognition classes; K is a set of frames of a digital image of a region; $Y^{|M|}$ is an input training matrix, where M is a cardinal number; $X^{|M|}$ is a working binary training matrix that adapts to its maximum accuracy during the machine learning process; f_1 is an operator for forming the input training matrix $Y^{|M|}$; f_2 is a transformation operator of the input Euclidean training matrix $Y^{|M|}$ into the working binary training matrix $X^{|M|}$ formed in Hamming space.

Figure 1 shows the functional categorical model of information-extreme machine learning on a linear data structure with optimization of parameters of the vector (1).

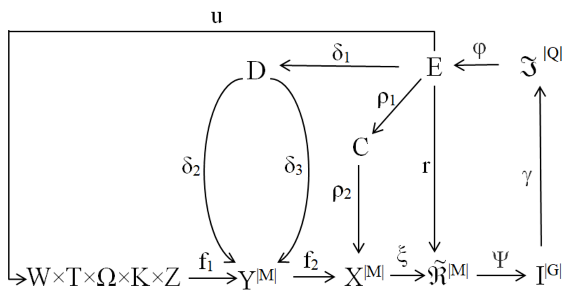

Fig. 1. Functional categorical machine learning model based on linear data structure

In Figure 1, the operator ξ displays binary vectors of the working training matrix $X^{|M|}$ for a divison $\Re^{|M|}$ of recognition classes. The classification operator ψ tests the underlying statistical hypothesis $\gamma_1 : x_{m,i}^{(j)} \in X_m^o$. Operator γ forms a set $\Im^{|Q|}$ for accuracy characteristics of classification solutions, where $Q = G^2$, and the operator φ calculates the set of values E of the information optimization criterion, which is a function from the accuracy characteristics. The operator r restores the recognition class partition $\Re^{|M|}$ at each step of machine learning. The optimization loop of control tolerances for recognition features is closed by the term set D. At the same time, the operator δ_1 sets the control tolerance values at each step of machine learning. The operator δ_2 changes the control tolerances for all recognition features at each step of machine learning during their parallel optimization, and the operator δ_3 accordingly changes the control tolerances for the i-th characteristic during their sequential optimization. The optimization contour for the selection level of coordinates of averaged binary vectors of recognition classes is closed by the term-set C of selection level values. In this circuit, the operator ρ_1 sets the value of the selection level, and operator ρ_2 forms the averaged binary feature vectors of the recognition classes. The machine learning process is regulated by operator u.

According to the FCM (fig. 1), the deep information-extreme machine learning algorithm with optimization of the selection level for coordinates of averaged binary recognition feature vectors for the training matrix is represented as an iterative procedure

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for searching the global extremum of the information criterion (2) within the working domain of its function definition.

$$\rho^* = \arg\max_{G_\rho}\{\max_{G_{\delta_i}}\{\max_{G_\delta}\{\max_{G_E \cap G_d} \frac{1}{M}\sum_{m=1}^{M} E_m(d)\}\}\}, \quad (3)$$

where G_ρ is the range of permissible values of the selection level for coordinates of averaged binary vectors of training matrices for recognition classes; G_{δ_i} is the range of permissible values of the parameter δ_i of the control tolerance field for the i-th recognition feature; G_δ is the range of permissible values of parameter δ of the control tolerance field for recognition features.

The iterative procedure (3) determines the bottom of the depth of information-extreme machine learning. According to the principle of deferred decisions by O. G. Ivakhnenko, machine learning does not necessarily reach a given depth, since decision rules that are error-free according to the training matrix can be built at a smaller depth. Therefore, information-extreme machine learning begins with the second level of depth, at which the basic two-cycle procedure for finding the global maximum of the information optimization criterion is implemented:

$$\delta^* = \arg\max_{G_\delta}\{\max_{G_E \cap G_d} \frac{1}{M}\sum_{m=1}^{M} E_m(d)\}, \quad (4)$$

where G_δ is the range of permissible values of parameter δ.

According to procedure (4), at the first depth level, the geometric parameters of the hyperspherical containers of the recognition classes are optimized, and at the second, the control tolerances for the recognition features are optimized in parallel.

The input information for the machine learning algorithm is the training matrix array $\{y^{(j)}_{m,i}\}$, system of normalized tolerance fields $\{\delta_H\}$ for recognition features, which specifies the range of values of the corresponding control tolerances, and the selection level ρ of the coordinates of the averaged binary feature vectors of the recognition classes, which by default is equal to 0.5.

Following are the main stages of implementing the UAV machine learning algorithm according to procedure (5) with parallel optimization of control tolerances for recognition features:

1) resetting the recognition class counter: $m := 0$;

2) $m : m+1$;

3) resetting the parameter change counter δ : $\delta := 0$;

4) $\delta := \delta + 1$;

5) the lower $A_{HK,i}$ and upper $A_{BK,i}$ control tolerances for recognition features are calculated according to the rules

$$A_{HK,i} = y_i - \delta; \quad A_{BK,i} = y_i + \delta, \quad (5)$$

where y_i is an averaged (nominal) value of the i-th recognition feature;

6) resetting the counter of steps of changing the radius of the hyperspherical container of the recognition class: $k := 0$;

7) $k := k = 1$;

8) forming a three-dimensional array of binary training matrix $\{x^{\{j\}}_{m,i}\}$, whose elements are calculated according to the rule

$$x^{(j)}_{m,i}[d] = \begin{cases} 1, \text{ if } A_{HK,i}[k] < y^{(j)}_{m,i} < A_{BK,i}[k]; \\ 0, \text{ if else;} \end{cases}$$

9) formation of an array of averaged binary realizations $\{x_m\}$, whose elements are determined by the rule

$$x_{m,i} = \begin{cases} 1, & \text{if } \dfrac{1}{n}\sum_{j=1}^{n} x^{(j)}_{m,i} > \rho_m; \\ 0, & \text{if else;} \end{cases}$$

where ρ_m is a quantization level of binary vector coordinates x_m, which defaults to 0.5.

10) partitioning a set of vectors $\{x_m\}$ into pairs of nearest neighbors;

11) the information optimization criterion is calculated (2);

12) if $k < d(x_m \oplus x_c)$, where $d(x_m \oplus x_c)$ is inter-center code distance for nearest neighboring recognition classes X^o_m i X^o_c, then step 13, otherwise step 7;

13) if $\delta = \delta_H$, then step 14, otherwise step 4;

14) the maximum value of the information criterion in the working (allowable) area of its function definition is determined;

15) if m = M, then step 16, otherwise step 2;

16) the global maximum of the averaged information criterion $\overline{E}^*$ is determined in the workspace of its function;

17) the optimal parameters given by the vector (1) are determined:

$\{x^*_m \mid m=\overline{1,M}\}$ are the optimal average feature vectors of recognition classes from a given alphabet;

$\{d^*_m \mid m=\overline{1,M}\}$ are the optimal radii of recognition class containers;

δ^* is the optimal parameter of the control tolerance field for recognition features;

18) according to formula (6) by parameter δ^* the optimal lower $\{A^*_{HK,i} \mid i=\overline{1,N}\}$ and upper $\{A^*_{BK,i} \mid i=\overline{1,N}\}$ control tolerances for recognition features are calculated:

$$A^*_{HK,i} = y_{m^*} - \delta^*;\ A^*_{BK,i} = y_{m^*} + \delta^*;$$

19) STOP.

As a criterion for optimizing machine learning parameters, the modified Kullback-Leibler information measure was considered in the form [15]:

$$K_m(d) = \frac{1}{n_{min}}\{n_{min} - [K_{1,m}(d) + K_{2,m}(d)]\} \times \\ \times \log_2\left\{\frac{2n_{min} - \left[K_{1,m}(d) + K_{2,m}(d)\right] + 10^{-\lambda}}{\left[K_{1,m}(d) + K_{2,m}(d)\right] + 10^{-\lambda}}\right\}, \tag{6}$$

where $K_{1,m}(d)$ is the number of events in which recognition class X^o_m vectors are mistakenly not assigned to it; $K_{2,m}(d)$ is a number of events in which vectors of another recognition class are mistakenly attributed to a recognition class X^o_m; n_{min} – minimum size of a representative training sample; $10^{-\lambda}$ is a sufficiently small number entered to avoid division by zero.

The normalized form of criterion (6) is represented as

$$E_m = \frac{K_m(d)}{K_{max}}, \tag{7}$$

where K_{max} is the maximum value of criterion (6) that it accepts when substituting $K_{1,m}(d) = n_{min}$ and $K_{2,m}(d) = 0$.

The implementation of the basic algorithm (5) of information-extreme machine learning depending on the degree of intersection in the space of recognition class features does not always allow constructing error-free decision rules according to the training matrix. In this case, according to the procedure (4), it is necessary to increase the level of depth by sequentially optimizing the control tolerances for recognition features according to the scheme

$$\delta^*_i \mid i=\overline{1,N}\} = \arg \bigotimes_{l=1}^{L} \max_{G_{\delta_i}}\{\max_{G_\delta}\{\max_{G_E \cap G_d} \frac{1}{M}\sum_{m=1}^{M} E_m(d)\}\}, \tag{8}$$

where $\otimes$ is a symbol for repeating the procedure (8); L is the number of runs of the iterative procedure for optimizing the control tolerance system for recognition features; N is the number of recognition features.

Since in the process of optimizing the i-th feature, other subsequent features have suboptimal control tolerances, sequential optimization requires repeating the iterative procedure until the values of the information criterion for optimization stop changing. To increase the efficiency of machine learning, it is advisable to choose the optimal control tolerances obtained during parallel optimization as starting ones. In this case, the values of the information criterion for optimization calculated at each step of machine learning are constantly in the working area of determining its function.

The main stages of implementing the algorithm for sequential optimization of control tolerances for recognition features are:

1. $s := 0$.
2. $s := s+1$.
3. Resetting the recognition feature counter: $i := 0$.
4. $i := i+1$.
5. Determining the optimal parameter of the control tolerance field for the i-th recognition feature using procedure (5).
6. If $i \le N$, then step 4, otherwise step 7.
7. The maximum value of the information criterion $\overline{E}^{(s)}$ averaged over the alphabet of recognition classes is calculated.
8. If $\{[\overline{E}^{(s)} < E_{max}] \& (s < s_f)\}$, where s_f is a set amount of runs, then step 2, otherwise step 9.
9. The optimal parameters of the control tolerance field for recognition features are calculated by the assignment operation

$$\{\delta^*_i := \delta^{(s)}_i \mid i=\overline{1,N}\}.$$

10. According to formulas (6), the optimal lower and upper control tolerances are calculated.
11. Optimal machine learning parameters are memorized

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$\{x_m^* \mid m=\overline{1,M}\}$ are the optimal average feature vectors of recognition classes;

$\{d_m^* \mid m=\overline{1,M}\}$ are the optimal radii of recognition class containers;

$\{A_{HK,i}^* \mid i=\overline{1,N}\}, \{A_{BK,i}^* \mid i=\overline{1,N}\}$ are the optimal lower and upper control tolerances for recognition features.

12. STOP.

13. If the information criterion averaged over the alphabet of recognition classes does not reach its maximum value at the third level of machine learning depth, then it is necessary to move to the next level of depth. In our case, the outer loop of procedure (4) is implemented, in which the selection level ρ level changes within its permissible range at each step of machine learning. Based on the optimal geometric parameters of the recognition class containers obtained in the process of machine learning, decision rules are constructed, which in production form are represented as

$$
\begin{aligned}
&(\forall X_m^o \in \tilde{\Re}^{|M|})(\forall x^{(j)} \in \tilde{\Re}^{|M|})\{\text{if}[(\mu_m > 0)\,\& \\
&\mu_m = \max_{\{m\}}\{\mu_m\}] \text{ then } x^{(j)} \in X_m^o \text{ else } x^{(j)} \notin X_m^o\},
\end{aligned} \tag{9}
$$

where $x^{(j)}$ is a vector of recognition features; μ_m is a membership function of vector $x^{(j)}$ to the container of recognition class X_m^o.

In expression (9), the membership function for the hyperspherical container of the recognition class X_m^o is defined by the formula

$$\mu_m = 1 - \frac{d(x_m^* \oplus x^{(j)})}{d_m^*}, \tag{10}$$

where $d(x_m^* \oplus x^{(j)})$ is a code distance between vector x_m^* and vector $x^{(j)}$, which is being recognized.

Verification of the accuracy of machine learning by decision rules (9) is carried out in the functional testing mode. The task of functional testing is to verify the accuracy of decision rules built according to optimal geometric parameters. The functional testing algorithm is implemented according to the following scheme:

1) resetting the counter for recognition classes: $m := 0$;

2) initializing the counter for recognition classes: $m := m+1$;

3) calculating function (10)

4) if $m < M$, then step 2, otherwise step;

5) determining the maximal value of membersip function;

6) according to the decision rules (9), a decision is made on whether the feature vector $x^{(j)}$ belongs to one of the recognition classes of the given alphabet;

7) STOP.

The decision rules (9) constructed in the process of machine learning within the framework of the geometric approach are characterized by high efficiency and are practically invariant to the multidimensionality of the recognition feature dictionary due to their low computational complexity.

2.3. Hierarchical Information-Extreme Machine Learning

The disadvantage of machine learning based on a linear data structure is the decrease in accuracy as the alphabet of recognition classes increases. To increase the accuracy of information-extreme machine learning with more than two recognition classes, it is advisable to switch to using a hierarchical data structure in the form of a decursive binary tree. The construction of a decursive binary tree is carried out according to the following scheme:

1) for a given alphabet, a variational series of recognition classes is constructed by increasing the proximity criterion;

2) the variational series is divided into two groups, which respectively define two branches of the decursive binary tree;

3) as attributes of the vertices of the upper (first in dendrographic classification) tier of the decursive tree, the training matrices of the neighboring boundaries for each of the groups of recognition classes are selected;

4) attributes of vertices of the upper-tier stratum are transferred to vertices of the corresponding lower-tier child stratums;

5) as an attribute of another vertex of the lower tier stratum, the training matrix of the nearest neighbor in its group of recognition classes is selected;

6) the tree construction continues until strata containing training matrices of all recognition classes are formed.

Therefore, the binary decursive tree constructed according to the above scheme divides the given set of recognition classes into strata, each of which contains two nearest neighboring classes. As a result, for the two nearest neighboring recognition classes of each stratum, the above-considered information-extreme machine learning algorithm can be applied to the linear data structure with the required level of depth.

The input information description of the system learning from the decursive binary structure is represented as

$$I = < F, T, \Omega, K, Z, Y^{|M|}, H, Y^{|2|}_{h,s}, X^{|2|}_{h,s}; g_1, g_2, g_3, g_4 >$$

where H is a decursive binary tree; $Y^{|2|}_{h,s}$ is an input training matrix of two recognition classes for the stratum s of the h-th tier of decursive tree; $X^{|2|}_{h,s}$ is the working training matrix given in Hamming space; g_1 is the operator for forming the input training matrix $Y^{|M|}$; g_2 is the operator for constructing a recursive binary tree H; g_3 is the operator for forming the matrix $Y^{|2|}_{h,s}$; g_4 is the operator for forming the training matrix $X^{|2|}_{h,s}$.

Figure 2 shows the functional categorical model of machine learning based on a hierarchical data structure in the form of a decursive binary tree.

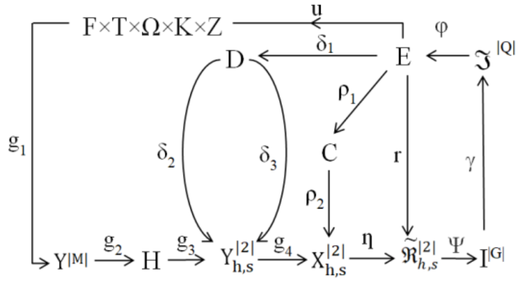


Fig. 2. Functional categorical model of hierarchical machine learning based on decursive data structure

Hierarchical functional categorical model differs from the machine learning model (Fig. 1) in the input mathematical description. In the process of hierarchical information-extreme machine learning, the operator η projects binary vectors of the working training matrix $X^{|2|}_{h,s}$ on a fuzzy, in general case, partition $\tilde{\Re}^{|2|}_{h,s}$ of two recognition classes for each stratum of the decursive tree. Next, the classification operator $\psi : \tilde{\Re}^{|2|} \to I^{|G|}$ tests the basic statistical hypothesis about the membership of a binary vector $x^{(j)}_{m,h,s}$ in a class $X^{o}_{m,h,s}$ and the information-extreme machine learning operators discussed above are implemented.

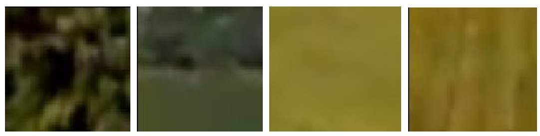
Therefore, constructing a decursive binary tree allows multi-class information-extreme machine learning to be reduced to two-class for each stratum, which is a necessary condition for increasing the accuracy of machine learning.

3. Experiments and Results

For machine learning of the onboard frame identification system, an image of the observation region obtained from aerial photography was selected (Fig. 3).

Fig. 3. Image of the region

Figure 4 shows selected frames of the image of the region (Fig. 3), which characterize the forest - recognition class X^{o}_{1}, field №1 – recognition class X^{o}_{2}, field №2 – recognition class X^{o}_{3} and field №3 – recognition class X^{o}_{4}.



a b c d

Fig. 4. Image frames: a – recognition class X^{o}_{1}; b – recognition class X^{o}_{2}; c – recognition class X^{o}_{3}; d – recognition class X^{o}_{4};

Analysis of Figure 3 shows that the brightness spectra of the selected image frames are close, which causes a priori fuzzy partitioning of recognition classes in the feature space and makes it difficult to achieve high accuracy of machine learning. Initially, information-extreme machine learning was implemented on a linear data structure with parallel optimization of control tolerances for recognition features, i.e. with a second level of depth according to procedure (5). At the same time, the normalized information criterion (7) was used to optimize the machine learning parameters.

Figure 5 shows a graph of the dependence of the alphabet-averaged recognition of the normalized information criterion (7) on the parameter of the control tolerance field, obtained in the process of information-

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extreme machine learning based on the linear data structure.

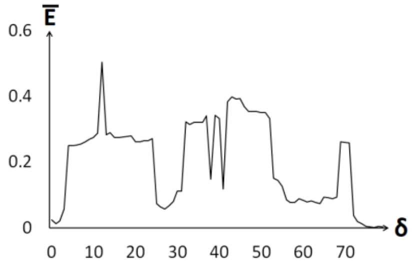

Fig. 5. Graph of the dependence of the information criterion on the parameter of the control tolerance field

Analysis of Figure 5 shows that the graph lacks the working (allowable) region for determining the information criterion function (7) for optimizing machine learning parameters, which indicates the indivisibility of recognition classes due to the high degree of their intersection in the recognition feature space. This fact determines the feasibility of switching to information-extreme machine learning with a hierarchical data structure in the form of a decursive binary tree. For this purpose, a variational series of recognition classes was previously constructed by increasing the average brightness of the training matrices of recognition classes (Fig. 6).

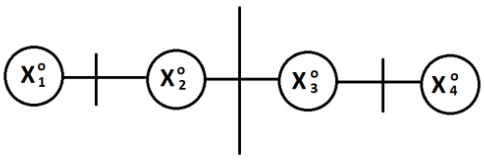

Fig. 6. Variational series of recognition classes

Figure 7 shows a decursive binary tree constructed using a variational series for a given alphabet $\{X^o_{m,h,s}\}$ of recognition classes.

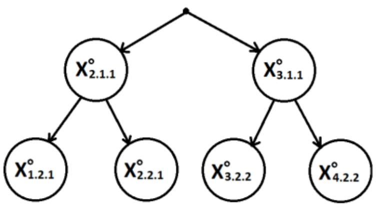

Fig. 7. Structure of a decursive binary tree

According to the above-described algorithm for constructing a decursive binary tree, the stratum recognition classes of the first (uppermost in dendrographic classification) tier are adjacent for two groups of the variation series (Fig. 6).

Figure 8 shows a graph of the dependence of the averaged information criterion $\overline{E}_{h,s}$ on the parameter $\delta_{h,s}$, obtained in the process of machine learning with parallel optimization of control tolerances for the features of the first-tier stratum recognition classes using procedure (5).

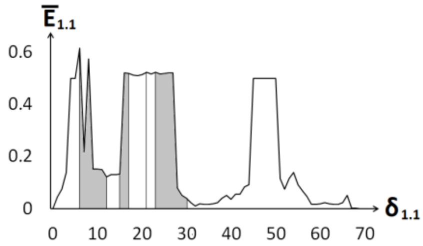

Fig. 8. Graph of the dependence of the information criterion on the parameter of the control tolerance field for the stratum of the upper tier of the decursive tree

Analysis of Figure 8 shows that the working (permissible) areas of the information criterion function definition have appeared on the graph, but the normalized information criterion does not reach its maximum limit value $\overline{E}^*_{h,s} = 1$, which does not allow constructing error-free decision rules based on the training matrix. To improve the accuracy of machine learning, its depth level was increased by sequentially optimizing the control tolerances for recognition features using an iterative procedure for finding the global maximum of the information criterion.

$$\{\delta^*_{h,s,i} \mid i = \overline{1,N}\} = \arg\left[\bigotimes_{l=1}^{L} \max_{G_\delta}\{\max_{G_E \cap G_d} \overline{E}^{(l)}_{h,s}(d)\}\right], \tag{11}$$

where $\overline{E}^{(l)}_{h,s}(d)$ is the average value of the information criterion for optimizing the machine learning parameters of the recognition classes of the s-th stratum on h-th tier of decursive; G_{δ_i} is the range of permissible values of the control tolerance field of the i-th recognition feature; G_E is an information criterion definition workspace; G_d is a range of permissible radius values $d_{m,h,s}$ for the container of recognition class $X^o_{m,h,s}$; $\otimes$ is a symbol of operation repetition; L is the amount of runs for procedure (11); i is the number of features in the structured vector of the recognition class training matrix $X^o_{m,h,s}$.

Figure 9 shows a graph of the change in the averaged normalized criterion (7), obtained as a result of sequential optimization of the parameter of the control tolerance field for recognition features according to procedure (11).

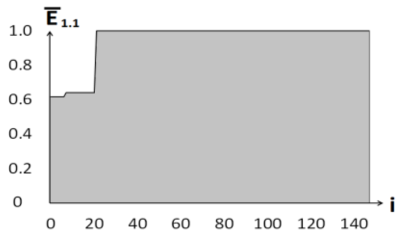

Fig. 9. Graph of changes in the information criterion in the process of sequential optimization of control tolerances for the upper tier stratum

Analysis of figure 9 shows that the information criterion reaches its peak value on the first iteration of procedure (11), number of which is determined by the ratio of iterations to recognition features. Figure 10 shows a graph of the dependence of the information criterion (7) on the parameter $\delta_{2,1}$ of the field of control tolerances for recognition features, obtained in the process of machine learning with parallel optimization of control tolerances for the features of recognition classes at the first stratum of the decursive tree's lower tier.

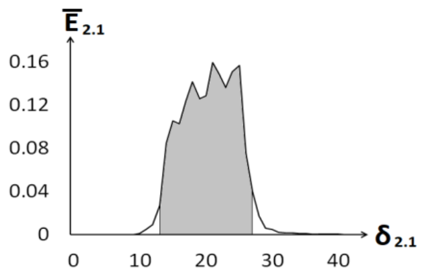

Fig. 10. Graph of dependence of the information criterion on the width of control tolerance field at the lower tier's first stratum

Graph analysis shows that the peak value of information criterion is low. In this case, the depth of machine learning was increased by sequentially optimizing the control tolerances for recognition features according to the procedure (11). Figure 11 shows the graph of the change in the information criterion (7), obtained in the process of information-extreme machine learning with sequential optimization of the control tolerances for recognition features.

Analysis of Figure 11 shows that the maximum value of the normalized information criterion has increased, but remains low. Therefore, the depth of machine learning was increased by optimizing the level of selection of coordinates of averaged binary vectors of recognition classes according to procedure (4).

Figure 12 shows a graph of the dependence of the averaged normalized information criterion (7), obtained in the process of information-extreme machine learning with optimization of the level of selection of coordinates of averaged binary vectors of recognition classes after sequential optimization of control tolerances for recognition features. At the same time, the values of the selection level on the graph changed in the interval [0.3; 0.7].

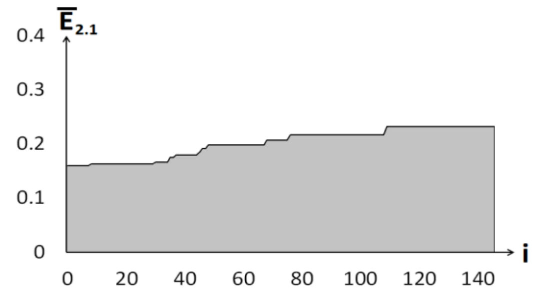

Fig. 11. Graph of changes in the information criterion in the process of sequential optimization of control tolerances for the first stratum of the lower tier of the decursive tree

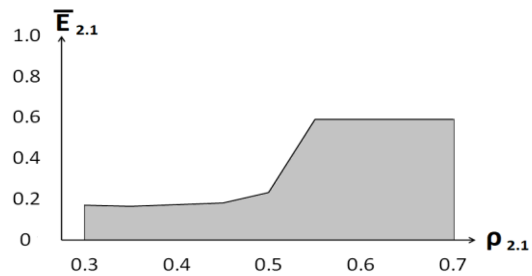

Fig. 12. Graph of dependence of information criterion on the selection level for recognition classes at the lower tier's first stratum

Analysis of Figure 12 shows that at this depth level the maximum value of the information criterion has increased to 0.60, but does not reach its limit value. This fact allows us to conclude that the partition of recognition classes constructed based on the results of machine learning remains indeterminate. Therefore, the idea arose to implement information-extreme machine learning with optimization of the level of selection of coordinates of binary vectors representing recognition classes of the first stratum of the lower tier between parallel and sequential optimization of control tolerances.

Figure 13 shows a graph of the dependence of the information criterion (7) on the selection level $\rho_{h,s}$, obtained in the process of information-extreme machine learning after parallel optimization of control tolerances for the first stratum of the lower tier.

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Analysis of Figure 13 shows that the maximum value of the normalized information criterion has significantly increased compared to the result of the basic information-extreme machine learning algorithm and is equal to $\overline{E}^*_{2,1} = 0{,}55$ at the optimal selection level $\rho^*_{2,1} = 0{,}40$. To improve the accuracy of machine learning, the level of its depth was increased, at which information-extreme machine learning was carried out with sequential optimization of control tolerances for recognition features. Figure 14 shows a graph of the change in the information criterion (7), obtained in the process of information-extreme machine learning with sequential optimization of control tolerances for recognition features at the optimal selection level $\rho^* = 0{,}4$.

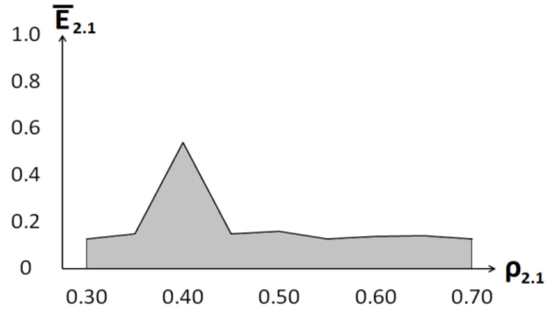

Fig. 13. Graph of dependence of criterion on the selection level for recognition classes at the lower tier's first stratum

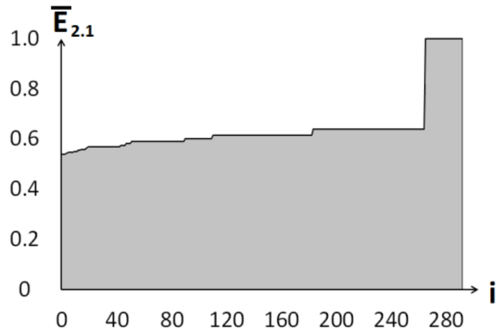

Fig. 14. Graph of changes in the information criterion in the process of sequential optimization of control tolerances for the first stratum of the lower tier

Analysis of Figure 14 shows that in the second run of procedure (11) the averaged information criterion reaches its maximum limit value.

Figure 15 shows a graph of the dependence of the normalized information criterion (7) on the parameter of the field of control tolerances $\delta_{2,2}$ for recognition features, obtained in the process of machine learning with parallel optimization of control tolerances for features of recognition classes of the second stratum of the second (lower) tier.

Analysis of Figure 15 shows that for the recognition classes of the second stratum of the second tier, the normalized information criterion reaches its maximum value $\overline{E}^*_{2,2} = 1$, which allows us to construct error-free decision rules based on the training matrix.

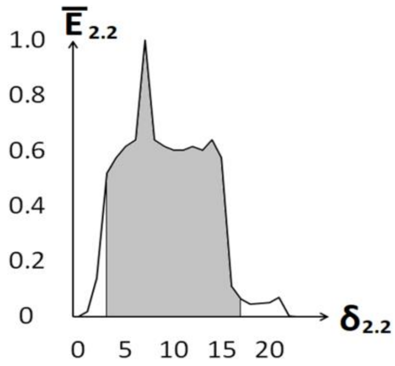

Fig. 15. Graph of the dependence of the information criterion on the parameter of the control tolerance field for the second stratum of the lower tier of the decursive tree

So, for all strata of the decursive tree (Fig. 6) based on the results of two-class information-extreme machine learning, error-free decision rules for vectors from the input training matrix were constructed.

To form the membership functions (10), it is necessary to determine the optimal geometric parameters of the recognition class containers. Figure 16 shows graphs of the dependence of the normalized criterion (7) on the radii of the recognition class containers of the strata of the decursive binary tree (Fig. 6).

Since in the process of information-extreme machine learning on a decursive data structure, the optimization of the radii of the average containers in the variational series of recognition classes occurs in two strata with different nearest neighbors, the smallest extreme value of the radii must be taken as the optimal one.

In addition, according to the minimum distance principle of recognition theory, in the case of several extreme values of the radii of the containers of recognition classes, the smaller value must be chosen as the optimal one. As a result, the decision rules of the recognition classes will have the following optimal radii of their hyperspherical containers, respectively: $d^*_1 = 53$ (hereinafter in code units) $d^*_2 = 52$, $d^*_3 = 10$ and $d^*_4 = 28$.

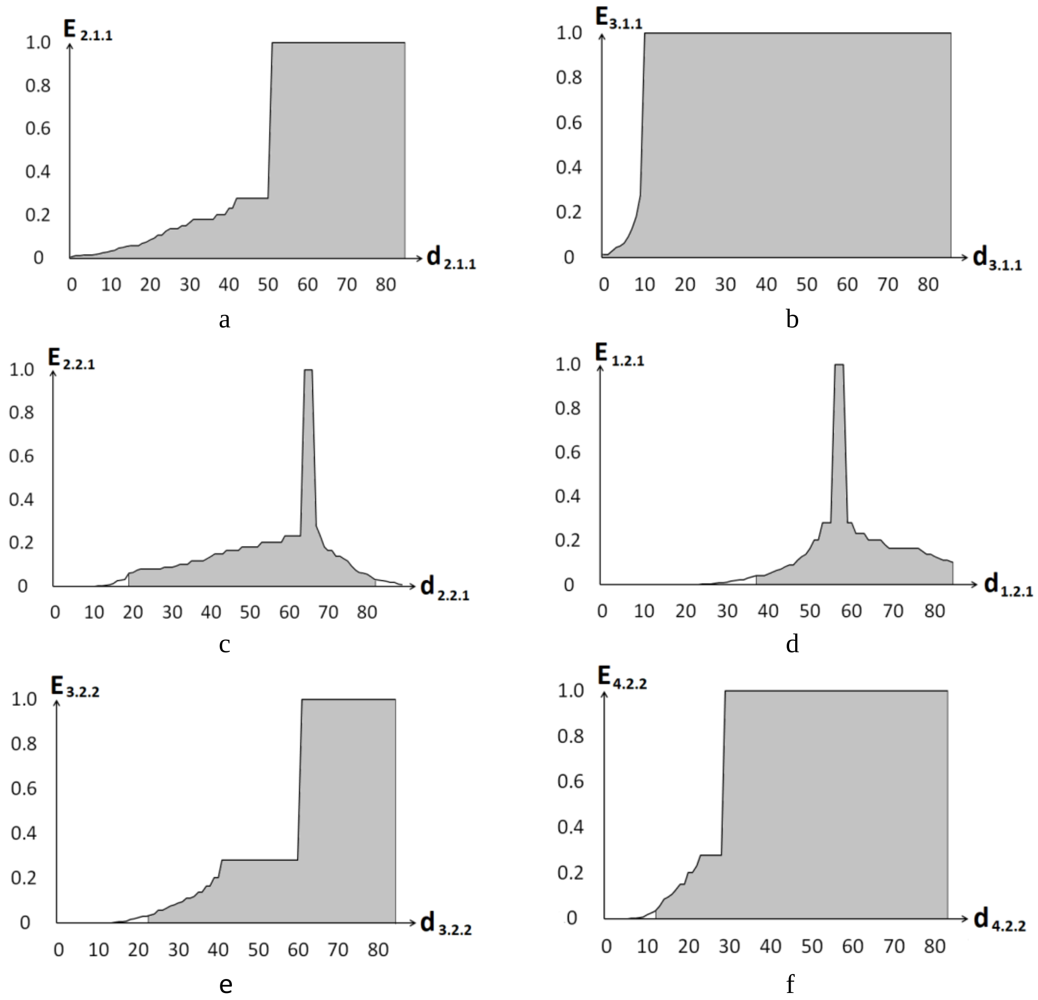

Fig. 16. Graphs of the dependence of the information criterion on the radii of containers: a – recognition class $X^o_{2,1,1}$; b – recognition class $X^o_{3,1,1}$; c – recognition class $X^o_{2,2,1}$; d – recognition class $X^o_{1,2,1}$; e – recognition class $X^o_{3,2,2}$; f – recognition class $X^o_{4,2,2}$

The accuracy of decision rules was checked in the functional testing mode. For comparison with other machine learning technologies, a typical artificial neural network with backpropagation of error was chosen. In order to create equal conditions for the experiment, the training matrix used in information-extreme machine learning was provided as input to the neural network. The results of the functional testing are presented in Table 1.

Table 1

Testing results

Method	Accuracy	Sensitivity	Specificity	F1-score	AUC-ROC
IEI-technology	0,97	0,96	0,98	0,95	0.97
ANN	0,78	0,75	0.79	0,74	0,75

The analysis of Table 1 shows that the obtained results for the proposed information-extreme machine learning method demonstrate high average values of standard accuracy metrics. Notably, the high sensitivity and specificity reflect the system's capability to minimize Type I and Type II errors, respectively. The AUC-ROC value, being close to 1, confirms high-quality classification achieved for all target classes. For the neural network, the lower values of standard accuracy metrics can be attributed to the limited size of the training matrix, which constrained performance improvement. In addition, unlike information-extreme machine learning methods, neural-like architectures exhibit limitations such as reduced flexibility, interpretability, and uniformity.

4. Discussion

The results of computer modeling demonstrated that, during the process of information-extreme machine

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learning using a hierarchical data structure in the form of a decursive binary tree at the fourth level of depth, it was possible to construct decision rules that produced zero errors on the training matrix. It was also experimentally shown that achieving high accuracy requires adherence to the principle of variability in the deep information-extreme machine learning strategy. For example, analysis of Figure 10 showed that optimizing the selection level of the coordinates of binary averaged vectors of recognition classes after parallel-sequential optimization of control tolerances did not lead to high machine learning accuracy. Therefore, the selection level of the coordinates of binary vectors was instead optimized between the parallel and sequential stages of control tolerance optimization. This resulted in an increase in the maximum value achieved for the information criterion, averaged over the recognition class alphabet. This fact is explained by the algorithm of sequential optimization being sensitive to the starting values of control tolerances obtained from the results at the previous depth level of information-extreme machine learning. The main limitation of the proposed method of deep information-extreme machine learning based on a decursive data structure is the use of hyperspherical containers for recognition classes. This assumption is justified in the case of a Gaussian distribution of class vectors relative to their geometric centers. However, if the empirical distribution deviates from the Gaussian model, more complex forms of radial basis containers for recognition classes must be used, such as hyperellipsoidal, hypercylindroidal, and others.

5. Conclusions

The problem of information synthesis of the onboard system of an autonomous UAV for identifying frames of a digital image of a region was solved based on machine learning. As a result of the conducted research, the following results were obtained:

1. For the first time, a method of deep information-extreme machine learning based on a hierarchical data structure in the form of a decursive binary tree has been developed, which, unlike the known ones, additionally optimizes the selection level of the coordinates of binary averaged recognition feature vectors, which define the geometric centers of recognition classes in a Hamming space, and allows:

– to move from multi-class machine learning to two-class for each stratum of a decursive binary tree, which creates the necessary conditions for increasing the accuracy of classification decisions;

– for a given alphabet of recognition classes, construct, within the framework of a geometric approach, error-free decision rules based on the training matrix, which are characterized by high efficiency in making classification decisions.

2. It is experimentally proven that deep information-extreme machine learning requires optimization of its implementation plan. It is shown that optimization of the selection level of coordinates of binary averaged realizations of recognition classes after parallel-sequential optimization of control tolerances did not allow to achieve high accuracy of machine learning. At the same time, optimization of selection levels after parallel optimization of control tolerances and before their sequential optimization allowed to achieve the limiting maximum value of the information criterion averaged over the alphabet of recognition classes.

3. Further research will be conducted in two directions. The first involves increasing the depth of machine learning with a large capacity of the recognition class alphabet. The second direction focuses on investigating the impact of additional machine learning parameters on system performance, with an emphasis on optimizing the parameters for forming the input mathematical description.

Contribution of authors: development of conceptual provisions and methodology of research, formulation of conclusions – **Valerii Cheranovskyi**, **Mykyta Myronenko**; Review and analysis of references; development of software for modeling – **Serhii Kovalevskyi**, **Roman Kraskovskyi**; development of mathematical models, analysis of research results – **Mykhailo Otroshchenko**.

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Use of Artificial Intelligence: the authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, as described in the research methodology section.

All authors have read and approved the published version of this manuscript.

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ГЛИБОКЕ ІНФОРМАЦІЙНО-ЕКСТРЕМАЛЬНЕ МАШИННЕ НАВЧАННЯ АВТОНОМНОГО БПЛА ЗА ДЕКУРСИВНОЮ СТРУКТУРОЮ ДАНИХ ДЛЯ СЕМАНТИЧНОЇ СЕГМЕНТАЦІЇ ЦИФРОВОГО ЗОБРАЖЕННЯ РЕГІОНУ

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Предметом дослідження є функціональні категорійні моделі інформаційно-екстремального глибокого машинного навчання за лінійною та ієрархічною структурами даних, методи оптимізації параметрів машинного навчання за інформаційним критерієм та побудови декурсивного бінарного дерева даних для заданої абетки класів розпізнавання. **Метою** дослідження є підвищення точності машинного навчання автономного БПЛА для семантичної сегментації цифрового зображення регіону, отриманого за оптоелектронним каналом спостереження. Поставлена мета досягається шляхом розроблення методу глибокого інформаційно-екстремального машинного навчання бортової системи розпізнавання автономного БПЛА за декурсивною бінарною структурою даних. Розроблено **новий метод** глибокого інформаційно-екстремального машинного навчання автономного БПЛА за ієрархічною структурою даних у вигляді декурсивного бінарного дерева. Новизна методу полягає в максимізації середньої міжкласової кодової відстані в заданому вимірі простору ознак Геммінга шляхом оптимізації рівня селекції координат статистично усереднених двійкових реалізацій класів розпізнавання. При цьому рівень глибини інформаційно-екстремального машинного навчання згідно з принципом відкладених рішень визначається кількістю параметрів функціонування системи, що оптимізуються за інформаційним критерієм. Такий підхід на відміну від нейроподібних структур дозволяє надати бортовій системі розпізнавання, що навчається, гнучкості при перенавчанні у випадку розширення абетки класів розпізнавання. Як критерій оптимізації параметрів машинного навчання розглядається модифікована авторами інформаційна міра Кульбака-Лейблера. Крім того, запропонований метод передбачає трансформацію вхідної навчальної матриці у задану в просторі Геммінга робочу бінарну матрицю, яка в процесі машинного навчання адаптується до його максимальної точності. **Результати:** За результатами глибокого інформаційно-екстремального машинного навчання побудовано у рамках геометричного підходу безпомилкові за навчальною матрицею вирішувальні правила. Показано, що при глибокому інформаційно-екстремальному машинному навчанні на його точність впливає послідовність оптимізації параметрів функціонування системи розпізнавання. Результатами функціонального тестування та крос-валідації підтверджено високу точність інформаційно-екстремального машинного навчання автономного БПЛА на прикладі семантичної сегментації цифрового зображення регіону. **Висновки:** Вперше розроблено метод глибокого інформаційно-екстремального машинного навчання за ієрархічною структурою даних у вигляді декурсивного бінарного дерева, який на відміну від відомих додатково оптимізує рівень селекції координат двійкових усереднених векторів ознак розпізнавання.

Ключові слова: інформаційно-екстремальне машинне навчання; інформаційний критерій; оптимізація; автономний БПЛА; декурсивне бінарне дерево; цифрове зображення регіону.

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