Advances in Artificial Intelligence and Machine Learning; Research 5 (1) 3534-3547 Received 13-12-2024; Accepted 22-03-2025; Published 29-03-2025

Numerical Methods of Synthesis of a Correct Algorithm for Solving Recognition Problems

Islambek Saymanov islambeksaymanov@gmail.com
National University of Uzbekistan
Uzbekistan

Alimdzhan Babadzhanov a.babadjanov@uzmf.uz
Engineering Federation of Uzbekistan
Uzbekistan

Akmal Varisov a.varisov@argos.uz
Agency for Civil Service Development under the
President of the Republic of Uzbekistan
Uzbekistan

Nodirbek Urinov urinov@adu.uz
Andijan State University
Uzbekistan

Anvarxon Madjidov $19_{sim_9}2@mail.ru$
$National University of Uzbekistan,$
$Uzbekistan$

Corresponding Author: Islambek Saymanov

Abstract

We mainly study the voting model. The article considers recognition problems with disjoint classes. These problems are, in a particular case, a discrete analogue of the problem of finding optimal solutions. Not only the problems of synthesizing the best solutions, but also other important classes of applied problems are reduced to recognition problems. In real calculations, there is no need to remember all the parameters $P_{rv} \cdot \varepsilon_{rv}$ that determine the proximity function for the recognizable object and the sets K_j. It is enough to limit ourselves to only a small part. The values of the parameters $\varepsilon_{ik} P_{ik}$ in problems with disjoint classes are determined independently for each class.

In this paper, we describe methods that allow you to select the parameters $\varepsilon_{ik} P_{ik}$ depending on the values of the k-th feature a_{ik} on the objects of the original information. An algorithm for selecting the parameters P_{ik} that determine the proximity function for the recognizable object and the classes K_j has been developed. and the choice of parameters ε_{ik}, defining the proximity function in recognition problems with non-overlapping classes. A method for constructing a support set for a recognition algorithm in problems of classifying objects with disjoint classes has been proposed. A numerical method for finding optimal values

Citation: Islambek Saymanov, et al. Numerical Methods of Synthesis of a Correct Algorithm for Solving Recognition Problems. Advances in Artificial Intelligence and Machine Learning. 2025;5(1):202.

of the parameters $\varepsilon_{i_k} P_{i_k}$ defining the proximity function in recognition problems with non-overlapping classes based on solving systems of Boolean equations and searching for irreducible table coverage has been developed.

Keywords: Numerical method, Finding optimal values, Recognition, Non-intersecting classes, Systems of Boolean equations, Irreducible table coverage, Correct algorithm.

1. INTRODUCTION

In recent years, the solution of applied problems of classification, recognition and forecasting has received great development [1, 2]. In many real cases, the solution scheme remains the same, the set of possible solutions is divided into subsets in such a way that one subset includes solutions that are close in some metric [3, 4]. In the future, the solutions that fall into one subset are not distinguished, and all objects corresponding to these solutions are assigned to one class. Information is described past experience is presented in the following form: various objects are described in some way and their descriptions are divided into a finite number of non-overlapping classes. When a new object appears, a decision is made to assign it to one or another class. It is proposed to choose a generalized algorithm that would achieve extreme forecasting quality [5–7]. Let us consider algorithmic models for solving classification problems. Among these models, we can highlight the most common ones when solving applied problems. The article considers recognition problems with non-overlapping classes. To solve these problems by algebraic methods, the article proposes a computational algorithm that is much simpler in description and much more effective. These problems are, in a particular case, a discrete analogue of the problem of finding optimal solutions. Not only the problems of synthesizing the best solutions, but also other important classes of applied problems are reduced to recognition problems. In the algorithmic approach, it is shown that each algorithm A can be represented as $A = B \times C$ of two operators, a recognition operator B and a decision rule C [8–12].

The paper studies an algorithmic model for calculating estimates and proves the existence of an optimal algorithm in this model. For problems with non-overlapping classes, a computational algorithm that is much simpler in description and significantly more efficient is constructed [13]. Methods are developed that allow for more economical encoding of the operator B, which will reduce the required memory and more efficiently use the constructed correct algorithms for solving applied problems.

This paper investigates the parameters $\varepsilon_{ik} P_{ik}$, which determine the proximity function for the recognizable object and classes K_i (P_{rv} is the weight of the v-th feature in the reference object S_r) [14–17]. In problems with non-overlapping classes, the values a_{ik} are determined independently for each class. We will describe methods that allow us to select the parameters $\varepsilon_{ik} P_{ik}$ depending on the values of the k-th feature a_{ik} on the objects of the original information [18, 19].

To calculate the values of the parameters $\varepsilon_{ik} P_{ik}$, we will assign, as was done earlier, the sign (+) to the objects of the sequence if they belong to the class K_j. And the sign (-) if they belong to the class CK_j [20–27].

This allows us to write the sequence as follows:$S^{+i_1}, S^{-i_2}, S^{-i_3}, S^{+i_4}, S^{+i_5}, \ldots, S^{-i_q}$. Let the set of admissible objects be divided into two classes: $\tilde{K}_j$ and $C\tilde{K}_j$ [28–31]. Let it also be known that objects $S^1, \ldots, S^t$ belong to the class $\tilde{K}_j$, and objects $S^{t+1}, \ldots, S^q$ belong to the class $C\tilde{K}_j$.

This article solves the problem of optimal selection of parameters $P_{i_k}, \varepsilon_{i_k}$, which determine the proximity function in problems with disjoint classes.

A method for constructing a support set for a recognition algorithm in problems of classifying objects with non-intersecting classes is proposed. A numerical method for finding optimal values of the parameters $\varepsilon_{ik} P_{ik}$ that determine the proximity function in recognition problems with non-intersecting classes is developed based on solving systems of Boolean equations and searching for irreducible table coverage.

2. SELECTION OF PARAMETERS $P_{i_k}, \varepsilon_{i_k}$ DEFINING THE PROXIMITY FUNCTION IN PROBLEMS WITH DISJOINT CLASSES

2.1 Selection of Parameters P_{i_k}.

Consider the value $p_k(a_{ik}, b_{ik}), t = \overline{1, q}$, that is, the distance from the value k – that feature on the object S_n in the training table T_{nml}, then the values of the same feature in S^t from S^q:

$$p_k\left(a_{ik}, b_{ik}\right), \ldots, p_k\left(a_{ik}, b_{ik}\right) \in K_j \tag{1}$$

$$p_k\left(a_{ik}, b_{t+1}\right), \ldots, p_k\left(a_{ik}, b_{qk}\right) \in CK_j \tag{2}$$

When determining the parameter P_{i_k} in real problems, two cases are possible:

1. a_{ik} - value of k – th attribute in S_i and $S_i \in K_j$;
2. a_{ik} - value k – th feature in S_i and $S_i \in CK_j$;

In the first case, the parameters P_{ik} - are determined proportionally to the ratio of the sum of the distances from the k – th feature of the object S_i in the training table T_{nml}, to the values of that same feature in S^u from S^q, $S^u \in CK_j$ to the sum of the distances of feature k – object S_i in the training table T_{nml}, to the values of the same feature in S^u from $S^q \bigcap K_j$.

To avoid division by 0, we add 1 to the denominator. Then we determine the value of the weight P_{ik} using the formula:

$$P_{ik}^{01} = \frac{\left[p\left(a_{ik} b_{tk}\right) + \ldots + p_k\left(a_{ik} b_{qk}\right)\right]}{\left[p\left(a_{ik} b_{ik}\right) + \ldots + p_k\left(a_{ik} b_{tk}\right)\right] + 1} \tag{3}$$

In the second case, the value of the weight of the feature in the reference object is determined by the following formula:

$$P_{ik}^{02} = \frac{\left[p_k\left(a_{ik} b_{ik}\right) + \ldots + p_k\left(a_{ik} b_{tk}\right)\right]}{\left[p_k\left(a_{ik} b_{ik}\right) + \ldots + p_k\left(a_{ik} b_{qk}\right)\right] + 1} \tag{4}$$

We will also describe the second method of determining weights. Let us introduce the concept of a correct pair (S^w, S^v) $\left(S^w \in K_j\ S^v \in CK_j\right)$ for the sequence:

$$S^{+i_1}, S^{-i_2}, S^{-i_3}, \dots, S^{+i_q} \tag{5}$$

Definition: Pair (S^w, S^v) $\left(S^w \in K_j\ S^v \in CK_j\right)$ from the sequence $S^{+i_1}, S^{-i_2}, S^{-i_3}, \dots, S^{+i_q}$ is called correct with respect to (S^u, r) $u = u\,(v, w)$, $r = r\,(u, w)$ if

$$P_r\,(a_{ur}, b_{wr}) < P_r\,(a_{ur}, b_{wr})\ 1 \le v, w \le q, v \ne w, 1 \le r \le n \tag{6}$$

This means that the object $S^w \in K_j$ occurs earlier than the object $S^v \in CK_j$ in the sequence $S^{+i_1}, S^{-i_2}, S^{-i_3}, \dots, S^{+i_q}$.

In this case, P_{ur}^{01} is determined proportionally to the ratio of the number of correct pairs $N\,(I, k)$ to the total number of pairs $t \cdot (q - t)$, that is:

$$\frac{N\,(I, k)}{t \cdot (q - t)} = P_{ur}^{01}$$

Now, let's change the concept of a correct pair, and for this case we will calculate the value of the weight P_{ur}^{02}.

A pair (S^w, S^v) is called correct with respect to (S^u, r) if in the sequence $S^{+}, \dots, S^{-i_q}$ the object $S^v \in CK_j$ occurs earlier than $S^w \in K_j$. That is, for a pair (S^w, S^v), $S^w \in K_j$, $S^v \in CK_j$ from the sequence $S^{+i_1}, S^{-i_2}, S^{-i_3}, \dots, S^{+i_q}$ the feature r is such that:

$$P_r\,(a_{ur}, b_{ur}) < P_r\,(a_{ur}, b_{wr})\ 1 \le v, w \le q, v \pm w, 1 \le r \le n \tag{7}$$

Then the formula for determining P_{ur}^{02} will have the following form:

$$\frac{t \cdot (q - t)}{N\,(I, k)} = P_{ur}^{02} \tag{8}$$

We can define P_{ur}^{0} as the sum of all P_{ur}^{01} and P_{ur}^{02} by first selecting the parameters α and β as $\alpha + \beta = 1$, $\alpha P_{ur}^{01} + \beta P_{ur}^{02} = P_{ur}^{0}$, or as the product $P_{ur}^{0} = P_{ur}^{01} \cdot P_{ur}^{02}$.

2.2 Selection of Parameters ε_{ik}.

The proximity function $B\left(\Omega, S, K_j\right)$ is a threshold and depends on the values of the parameters S_{i_k}. Let's arrange the objects of the sequence $S^{+i_1}, S^{-i_2}, S^{-i_3}, S^{-i_4}, S^{+i_5}, \dots, \bar{S}^q$.

In ascending order of the value of $p\,(a_{ik}, b_{tk})\ t = \overline{1, q}$, we arrange the objects with equal element values in an arbitrary manner.

For pairs (S^w, S^v), $S^u \in K_j, S^v \in CK_j$ we define the values that separate these pairs. We take different values of ε_{ik} for:

$$p_{ik}\,(a_{iv}, b_{1k}), \dots, p_k\,(a_{ik}, b_{tk}) \tag{9}$$

$$p_{ik}\left(a_{ik}, b_{t+1,q}\right), \dots, p_k\left(a_{ik}, b_{qk}\right) \tag{10}$$

Let these values be equal to $\varepsilon_{ik}^1, \dots, \varepsilon_{ik}^{r(ik)}$.

For pairs (S^w, S^v), $S^u \in K_j, S^v \in CK_j$ the following cases are possible:

1. $p_k(a_{ik}, b_{uk}) = p_k(a_{ik}, b_{uk})$, then a_{ik} does not separate these pairs.
2. $p_k(a_{ik}, b_{ik}) > p_k(a_{ik}, b_{uk}), S_i \in K_j$ – does not separate
3. $p_k(a_{ik}, b_{ik}) < p_k(a_{ik}, b_{uk}), S_i \in K_j$ – divides

All parameters of the group ε^j, except for the parameters ε_{ik} are chosen so large that the inequalities are satisfied:

$$p_v(a_{rv}, b_{iv}) < \varepsilon_{rv}, i = 1, 2, \ldots, q \tag{11}$$

The parameters $\varepsilon_{ik}, i = 1, 2, \ldots, q$ are chosen so that the inequalities are satisfied:

$$p_k(a_{ik}, b_{ik}) \leq \varepsilon_{ik} \leq p_k(a_{ik}, b_{uk}) \tag{12}$$

Such a choice of parameters ε_{iu} occurs when $S^u \in K_j, S^v \in CK_j$. Thus, we obtain a partition using the threshold ε_{ik}, the values of which belong to the numerical half-segment composed of the values $[p_k(a_{ik}, b_{ik}) \leq p_k(a_{ik}, b_{vk})]$. When constructing algorithms for solving recognition problems, logical recognition methods are used, based on discrete analysis and propositional calculus based on it.

A new area of application of logic algebra methods is the problem of recognizing objects, where not only quantitative relationships between quantities characterizing the processes under consideration are essential, but also the logical dependencies connecting them.

A task for which the methods of logic algebra are applied can, for example:

- establishing various sets of features of a recognizable object, the consideration of which, along with already known ones, would lead to a certain conclusion about the type of object. The algorithm for recognizing objects based on logical methods was developed by Yu. M. Zhuravlev.

Let the set of objects $\{S\}$ be divided into classes $K_j, j = 1, \ldots, m$ and the features $i = 1, 2, \ldots, N$ are used to describe the objects.

All objects are described by the same set of features. Each of the features can take values from different sets: $\{0, 1\}$ 0-feature is not expressed, 1-feature is expressed; $\{0, 1, \Delta\}$ Δ - information about the feature is missing. The information is presented in the form of a training table T_{nml}.

The problem is as follows: It is necessary to find such ε_i that each pair (S^u, S^v) is separated at least once.

The solution to this problem can be reduced to finding solutions to Boolean algebraic equations

$$\varepsilon^1_{i_1 k_1} \bigcup \varepsilon^r_{i_2 k_2} \bigcup \ldots \varepsilon^{r_1}_{i_p k_p} \bigcup \ldots \bigcup \varepsilon^{r_2}_{i_2 k_2} \bigcup \ldots \bigcup = 1 \tag{13}$$

In order to preserve the form of the logical connection in the written form, we introduce a constraint for each group of logical terms $(i_1 k_1)(i_2 k_2) \ldots$ so that only one logical variable ε^2_{ik} takes values equal to 1 and the rest 0.

If we write such Boolean algebraic equations with the introduced restrictions on the Boolean variables for all objects from the set $\{S\}$, then we will reduce to a system of Boolean algebraic equations:

$$\varepsilon_{i_1k_1}^{1} \cdot \varepsilon_{i_1k_1}^{2} \cdot \ldots \cdot \varepsilon_{i_1k_1}^{r} \bigcup \varepsilon_{i_1k_1}^{1} \cdot \varepsilon_{i_1k_1}^{-2} \cdot \varepsilon_{i_1k_1}^{3} \cdot \ldots \cdot \varepsilon_{i_1k_1}^{r} \cup \bigcup \ldots \bigcup \varepsilon_{i_1k_1}^{1} \cdot \ldots \cdot \varepsilon_{i_1k_1}^{r-1} \cdot \varepsilon_{i_1k_1}^{-r} = 1 \tag{14}$$

$$\varepsilon_{i_1k_1}^{-1} \cdot \varepsilon_{i_1k_1}^{2} \cdot \ldots \cdot \varepsilon_{i_1k_1}^{2} \bigcup \varepsilon_{i_2k_2}^{1} \cdot \varepsilon_{i_2k_2}^{-1} \cdot \varepsilon_{i_2k_2}^{3} \cdot \ldots \cdot \varepsilon_{i_2k_2}^{r} \cup \bigcup \ldots \bigcup \varepsilon_{i_2k_2}^{1} \cdot \ldots \cdot \varepsilon_{i_2k_2}^{r-1} \cdot \varepsilon_{i_2k_2}^{-r} = 1 \tag{15}$$

$$\varepsilon_{i_1k_1}^{-1} \cdot \varepsilon_{i_1k_1}^{2} \cdot \ldots \cdot \varepsilon_{i_1k_1}^{2} \bigcup \varepsilon_{i_2k_2}^{1} \cdot \varepsilon_{i_2k_2}^{-1} \cdot \varepsilon_{i_2k_2}^{3} \cdot \ldots \cdot \varepsilon_{i_2k_2}^{r} \cup \ldots \bigcup \varepsilon_{i_nk_n}^{1} \cdot \ldots \cdot \varepsilon_{i_nk_n}^{r-1} \cdot \varepsilon_{i_1k_1}^{-r} \tag{16}$$

The solution of this system of Boolean algebraic equations will give us a set $\hat{\varepsilon}$ separating all pairs of the set of objects $\{S\}$. Two group of equations are actually necessary in order to preserve the basic structure of the previously described correct algorithms, in which any pair of control objects S^v, S^u is divided by a support set containing one pair (r, t), where $r = (u, v), t = t(u, v)$.

In real calculations, the formation of a system of pairs dividing objects of the control set can be done in a much less rigid way.

In the control population $\tilde{S}^q$, we select subsets $\tilde{S}^q \bigcap K, \tilde{S}^q \bigcap CK_j$ and denote them by $\tilde{K}_j, C\tilde{K}_j$. We take an arbitrary training object S_j and fix in it an object with feature t.

Case 1. $S_i \in K_j$. As before, let us consider the set of distances $p_t(a_{it}, b_{1t}), \ldots, p_t(a_{it}, b_{qt})$. It is easy to see that only values in the given sequence of distances can be selected as values of the parameter t. If we set $\varepsilon_{it} = p_t(a_{it}, b_{kt}), 1 \le k \le q$ or $\varepsilon_{it} = C_{it_k}$ then all objects S^u of the control sample for which $p_t(a_{it}, b_{ut}) \le C_{it_k}$ will receive a zero score. Therefore, it is desirable to choose the value C_{it_k} in such a way that the inequality is satisfied for the largest number of objects from $\tilde{S}^q$ belonging to the class K_j and, accordingly, is not satisfied for the largest number of objects not belonging to the class K_j, Z. Let's make a TABLE 1

Table 1: The largest number of objects that do not belong to class K_j

$p_t(a_{it}, b_{1t})$	$\ldots$	$p_t(a_{it}, b_{qt})$	If $\varepsilon_{it} = p(a_{it}, b_{wt})$
N_{11}	$\ldots$	N_{q1}	Number of objects for which the following have been completed (*)
N_{12}	$\ldots$	N_{q2}	Number of objects from CK_j for which inequality (*) is not satisfied

As an approximate value of ε_{it} we can take $p(a_{it}, b_{wt})$ for which the value

$$N_{1w} + N_{2w} \Rightarrow \max, W = \overline{1, q} \tag{17}$$

Case 2. $S^i \in CK_j$. Carrying out similar reasoning and denoting as in the table by N_{1w}, N_{2w} the number of objects of class K_j for which the inequality $p_t(a_{it}, b_{ut}) \le C_{it_w}$.

Is not satisfied and, accordingly, the number of objects of class CK_j for which it is satisfied, we arrive at the same selection condition: $N_{1w} + N_{2w} \Rightarrow \max, W = \overline{1, q}$.

The described procedure is computationally efficient and allows one to easily determine all thresholds ε_{it} in the recognition algorithm.

The threshold calculation algorithm ε_{it} described above may not provide sufficiently accurate recognition only in the case when the division by each feature covers a large part of the control objects, but a small part of the non-separable objects remains the same for all pairs. This is a fairly rare case, but it can still occur when solving practical recognition problems.

In such a situation, it is possible to use an algorithm that is more labor-intensive than the one described above, but less labor-intensive than the algorithm associated with solving a system of Boolean equations.

3. CONSTRUCTION OF A SUPPORT SET FOR THE RECOGNITION ALGORITHM

In the training table, the value of the k-th feature for the i-th object is allocated, i.e. the value is q_{ik}, and the entire column in the set of control objects is also allocated, i.e. values

$$b_{1k}, b_{2k}, \ldots, b_{qk}.$$

As noted earlier, as the value ε_{it} of the thresholds ε_{ik} one can consider only:

$$p_k\left(a_{ik}, b_{1k}\right), p_k\left(a_{ik}, b_{2k}\right), \ldots, p_k\left(a_{ik}, b_{qk}\right) \tag{18}$$

If among the latter there are identical numbers, then the total number of values ε_{ik} decreases accordingly. We will solve the problem of recognizing control objects, in which the training table consists only of elements a_{ik} and the column $b_{1k}, \ldots, b_{qk}$ is recognized. Recognition is carried out for a fixed class $K_j, 1 \leq j \leq l$. The simplest recognition rule is applied:

1) $S_i \in K_j$
   a) $p_k\left(a_{ik}, b_{2k}\right) \leq \varepsilon \Rightarrow$ assigns one vote for class K_j to object S^r.
   b) $p_k\left(a_{ik}, b_{2k}\right) > \varepsilon_1 \Rightarrow$ assigns one vote for class K_j to object S_0^2.
2) $S_i \in K_j$
   a) $p_k\left(a_{ik}, b_{2k}\right) > \varepsilon_{ik} \Rightarrow$ the object S^r is assigned one vote for the class K_j.
   b) $p_k\left(a_{ik}, b_{2k}\right) \leq \varepsilon_{ik} \Rightarrow$ the object S_0^2 is assigned a vote for the class K_j.

For given numbers (i, k) and the selected value of ε_{ik}, the sets of all control objects $\mu\left(i, k, \varepsilon_{ik}\right)$ that received the vote in the above-described procedure one vote and a set $\tilde{K}_j$ of objects that actually belong to the class K_j.

Two sets are introduced:

$M^1\left(i, k, \varepsilon_{ik}\right) = M\left(i, k, \varepsilon_{ik}\right) \bigcap \tilde{K}_j$ - a set of objects incorrectly recognized by the described procedure.

The sets $M^1\left(i, k, \varepsilon_{ik}\right), M^2\left(i, k, \varepsilon_{ik}\right)$ are formed by $i = \overline{1, m}, k = \overline{1, n}$, $\varepsilon_{ik} = p_k\left(a_{ik}, b_{1k}\right), \ldots,$ $p_k\left(a_{ik}, b_{qk}\right)$ thus the total number of sets $M^1\left(i, k, \varepsilon_{ik}\right) = M^2\left(i, k, \varepsilon_{ik}\right)$.

Does not exceed the value $n \cdot m \cdot q$.

Let

$$\tilde{M} = \bigcap_{\substack{i=\overline{1,m} \\ k=\overline{1,n}}} M^2\left(i, k, \varepsilon_{ik}\right), \varepsilon_{ik} = p_k\left(a_{ik}, b_{1k}\right), \ldots, p_k\left(a_{ik}, b_{qk}\right) \tag{19}$$

The non-emptiness of the set $\tilde{M}$ means that there is a control object incorrectly recognized by all a_{ik} for all possible values of ε_{ik}.

Otherwise, the construction can be carried out without resorting to a rather cumbersome general theory.

4. RECOGNITION ALGORITHM FOR THE CASE WHEN THE SET IS EMPTY.

We fix the value (i, k, ε_{ik}). We associate this triple with a Boolean variable X_{ik}, ε_{ik} for each of the control objects belonging to the class K_j. We select triples (i, k, ε_{ik}) on which this object is recognized correctly. The set of such triples for the object S^2 is denoted by $\mathfrak{M}_2$. Forms a logical equation $VX_{ik}, \varepsilon_{ik} = 1; X_{ik}, \varepsilon_{ik} \in \mathfrak{M}_2$.

In other words, we require that the support set of numbers (i, k) includes at least one pair (i, k) for which the object is recognized correctly. By varying r, we obtain the system

$$\begin{cases} VX_{ik}, \varepsilon_{ik} = 1; \\ X_{ik}, \varepsilon_{ik} \in \mathfrak{M}_2; \\ r = \overline{1, q} \end{cases} \tag{20}$$

The existence of at least one solution to this system is ensured by the emptiness of the set $\tilde{M}$.

System (20) exactly coincides with the systems describing the construction of dead-end tests; therefore, any algorithm for synthesizing all or some part of the dead-end tests can be used to solve it. If in test theory it is customary to characterize a dead-end test by its length (the number of elements in the test), then in this case the selection of the best dead-end test should be carried out according to another criterion.

Let a solution of system (20) be selected in which the unknown with numbers from the set $\{i, k, \varepsilon_{ik}\} = Q$ has received the value 1.

When carrying out the procedure with a single training element a_{ik} and a threshold ε_{ik}, we fix the number of errors on the control equal to:

$$m : (a_{ik}, \varepsilon_{ik}) \tag{21}$$

Then the total number of errors with separate use of elements from Q is obviously equal to:

$$(Q) = \sum_{\{i,k,\varepsilon_{ik}\}Q} m\left(a_{ik}, \varepsilon_{ik}\right) \tag{22}$$

It is required to select a solution (dead-end test) for which the value $m(a)$ is minimal. To reduce the search when solving the system, first for each pair (i, k) the value (i, k) is fixed that gives the minimal number of errors, and then only the numbers of the training elements are varied in the system.

The solution to the system will yield a set of numbers (ε_{ik}, i, k) that make up the support set in the voting algorithm.

5. NUMERICAL METHOD FOR FINDING OPTIMAL VALUES OF PARAMETERS ε_{ik}, P_{ik}

We will describe methods that allow choosing optimal values of parameters ε_{ik}, P_{ik} depending on the k-th feature a_{ik} on the objects of the initial information.

The set of control objects is also divided into two classes $\tilde{K}_j$ and $C\tilde{K}_j$.

In the training table, the value of the k-th feature is allocated for the i -th object, i.e. values, the entire column in the set of control objects is also selected, i.e. the values:

$$b_{1k}, b_{2k}, \ldots, b_{qk} \tag{23}$$

Let's define an elementary procedure for selecting the calculation of votes.

Let us sum up all positive contributions when comparing $a_{ik}, b_{1k}, \ldots, b_{qk}$ and negative contributions by absolute value.

The total number of positive situations will be written:

$$\Gamma_{ik}^{+}(\varepsilon_{ik}, P_{ik}) = P_{ik} \tag{24}$$

The total number of negative situations will be written:

$$\Gamma_{ik}^{-}(\varepsilon_{ik}, P_{ik}) = |-P_{ik}| \tag{25}$$

The resulting sum of positive and negative situations depends linearly on the values of the object weight - $-P_{ik}$. The threshold values ε_{ik} are selected from the set:

$$p_k(a_{ik}, b_{1k}), p_k(a_{ik}, b_{2k}), \ldots, p_k(a_{ik}, b_{qk}) \tag{26}$$

If among these values there are identical threshold values ε_{ik}, then the total number of values ε_{ik}, is reduced.

Below we will describe a method that allows choosing the optimal value of ε_{ik} and thereby reducing the enumeration of the set of values $\{\varepsilon_{ik}\}$.

Let us consider two values ε_{ik}^1 and ε_{ik}^2 of the threshold ε_{ik}.

Let ε_{ik}^1 be no worse (better) than ε_{ik}^2.

$$\left(\varepsilon_{ik}^1 >> \varepsilon_{ik}^2, \varepsilon_{ik}^1 > \varepsilon_{ik}^2\right) \tag{27}$$

If these conditions are satisfied, then this can be written as a system of inequalities

$$\begin{cases} \Gamma_{ik}^{+}\left(\varepsilon_{ik}^{1}\right) \geq \Gamma_{ik}^{2}\left(\varepsilon_{ik}^{2}\right) \\ \Gamma_{ik}\left(\varepsilon_{ik}^{1}\right) \leq \Gamma_{ik}\left(\varepsilon_{ik}^{2}\right) \end{cases} \tag{28}$$

or

$$\begin{cases} \Gamma_{ik}^{+}\left(\varepsilon_{ik}^{1}\right) > \Gamma_{ik}^{2}\left(\varepsilon_{ik}^{2}\right) \\ \Gamma_{ik}\left(\varepsilon_{ik}^{1}\right) < \Gamma_{ik}\left(\varepsilon_{ik}^{2}\right) \end{cases} \tag{29}$$

Value chart ε_{ik} look like this FIGURE 1:

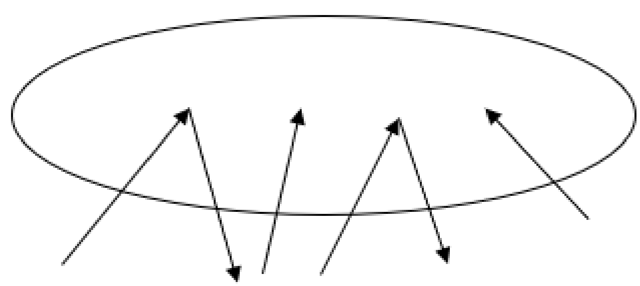

Figure 1: ε_{ik} value diagram

The resulting set will contain the best dominant values of the thresholds ε_{ik}.

The set of dominant values ε_{ik} will be denoted by $D\,(ik)$. This set will consist of the values $\{0, -P_{ik}, P_{ik}\}$ of the threshold ε_{ik} calculated in positive situations by a certain elementary procedure for choosing ε_{ik}.

The optimality of the chosen values of ε_{ik} is clearly demonstrated by the following theorem.

Theorem: $D\,(ik)$ *is the set of dominant values of the threshold* ε_{ik}*, consists of values of* ε_{ik} *with the same values of* $\Gamma_{ik}^{+}, \Gamma_{ik}^{-}$.

Proof Indeed, if we take some threshold value equal to $\varepsilon_{ik} = L_{ik}$, then we can write the following equality:

$$\Gamma^{+}\left(L_{ik}\right) + \left|\Gamma^{-}\left(L_{ik}\right)\right| = qP_{ik} \tag{30}$$

giving the total value of all contributions.

From the construction of the elementary procedure for calculating votes, namely from the property of calculating $-P_{ik}$ votes, it is clear that any increase in the sum of positive contributions $\Gamma^{+}\left(L_{ik}\right)$ automatically reduces the total value of negative contributions $\Gamma^{-}\left(L_{ik}\right)$ and thereby preserves the equality sign in (30), which proves the theorem. ■

Above, we considered methods that allow choosing the threshold value ε_{ik}. To fully define the proximity function $\left(\Omega, S, K_j\right)$ below we will consider methods that allow us to determine the value

Table 2: The value of the weights P_{ik} for the object S^i

P^j_{11}	P^j_{12}	$\dots$	P^j_{1n}
P^j_{21}	P^j_{22}	$\dots$	P^j_{2n}
$\vdots$	$\vdots$	$\vdots$	$\vdots$
P^j_{m1}	P^j_{m2}	$\dots$	P^j_{mn}

of the weight of the object P_{ik}. Let the value of the weights P_{ik} for the object S^i be given in the form of the following TABLE 2.

Let, as before, the set of metrics be divided into two classes:

$$P_k\left(a_{ik}, b_{ik}\right), \dots, P_k\left(a_{ik}, b_{ik}\right) \in K_j \tag{31}$$

$$P_k\left(a_{ik}, b_{t+1,k}\right), \dots, P_k\left(a_{ik}, b_{qk}\right) \in K_j \tag{32}$$

The problem of choosing the optimal value of the parameter P_{uv} can be reduced to solving a system of linear equalities, which can be written as follows form:

$$\begin{cases} \sum P^j_{uv} - \sum P^j_{rt} > 0 \\ \sum P^j_{uv} - \sum P^j_{rt} < 0 \end{cases} \tag{33}$$

Depending on whether the system is compatible or incompatible, we can consider two ways of solving the system of linear inequalities.

In the first case, we should return to linear closure.

In the second case, the algorithm for selecting the maximum compatible subsystem and solving it should be used.

The problem can also be reduced to solving a linear programming problem. There is a system of linear inequalities and one simple constraint on the variables $P^j_{uv} \geq 0$.

When solving this linear system of inequalities, the inconvenience is that two opposite optimization laws $\max$ and $\min$ operate here:

$$\begin{cases} \sum P^j_{uv} - \sum P^j_{rt} > 0 \\ \sum P^j - \sum P^j_{rt} < 0 \end{cases} \tag{34}$$

or

$$\begin{cases} \sum_1 \Rightarrow \max \\ \sum_2 \Rightarrow \min \end{cases} \tag{35}$$

under the constraint on the variables $P^j_{iv} \geq 0$.

But these difficulties can be overcome by multiplying by -1 the equations to which the minimization law applies, and thus the problem is reduced to solving a system of linear inequalities, where a single maximization law applies to the entire system with one simple constraint on the variables

$$\begin{cases} P^j_{iv} \geq 0 \\ \sum_1 - \sum_2 \Rightarrow \max \end{cases} \tag{36}$$

which can be solved by the simplex method, which will allow us to determine all the values of the weight P_i and thereby complete the definition of the proximity function $B\left(\Omega, S, K_j\right)$ for the recognizable object.

6. CONCLUSION

A method has been developed for choosing parameters P_{ik} that define the proximity function for the object being identified and classes K_j, as well as for selecting parameters ε_{ik} which characterize the proximity function in recognition tasks involving non-overlapping classes.

A method for constructing a support set for a recognition algorithm in problems of classifying objects with non-overlapping classes is proposed.

A numerical method for finding optimal values of parameters $\varepsilon_{ik} P_{ik}$ that determine the proximity function in recognition problems with non-overlapping classes is developed based on solving systems of Boolean equations and searching for irreducible table coverage.

References

[1] Shary SP, Zhilin SI, Simple Fast and Reliable Methods for Maximization of Recognizing Functional. J Comp Technol. 2023;28:87-100.

[2] Dou Q, Wei L, Magee DR, Cohn AG. Real-Time Hyperbola Recognition and Fitting in Gpr Data. IEEE Trans Geosci Remote Sensing. 2017;55:51-62.

[3] Zhuravlev YI, Ryazanov VV, Aslanyan LH, Sahakyan HA. On a Classification Method for a Large Number of Classes. Pattern Recognit Image Anal. 2019;29:366-376.

[4] Bondarenko NN, Yu Z.I. Algorithm for Choosing Conjunctions for Logical Recognition Methods. Comp Math Math Phys. 2012;52:649-652.

[5] Kabulov A, Baizhumanov A, Saymanov I. Synthesis of Optimal Correction Functions in the Class of Disjunctive Normal Forms. Mathematics. 2024;12:2120.

[6] Kabulov A, Baizhumanov A, Berdimurodov M. On the Minimization of K-Valued Logic Functions in the Class of Disjunctive Normal Forms. J Math Mech Comput Sci. 2024;121:37-45.

[7] Kabulov A, Saymanov I, Babadjanov A, Babadzhanov A. Algebraic Recognition Approach in Iot Ecosystem. Mathematics. 2024;12:1086.

[8] Jalali M, Morteza Z, Abdolali B. Deterministic Solution of Algebraic Equations in Sentiment Analysis. Multimedia Tool Appl. 2023;82:35457-35462.

[9] Thai-Nghe N, Thanh-Hai N, Chi N. Deep Learning Approach for Forecasting Water Quality in IOT Systems. Int J Adv Comput Sci Appl. 2020;11:686-693.

[10] Ntizikira E, Wang L, Chen J, Saleem K. Enhancing Iot Security Through Emotion Recognition and Blockchain-Driven Intrusion Prevention. Internet Things. 2025;29:101442.

[11] Mittal H, Tripathi AK, Pandey AC, Venu P, Menon VG, et al. A Novel Fuzzy Clustering-Based Method for Human Activity Recognition in Cloud-Based Industrial Iot Environment. Wirel Netw. 2024;30:4365-4377.

[12] Mohapatra AD, Aggarwal A, Tripathy RK. Automated Recognition of Hand Gestures From Multichannel EMG Sensor Data Using Time–Frequency Domain Deep Learning for IoT Applications. IEEE Sens Lett. 2024;8:1-4.

[13] Kollu VN, Sharma GK, Kautish S, Manikandan R. Pattern Recognition Based Skin Lesion Stage Analysis Using IOT. SN Comput. 2024;5:473.

[14] Luo J. Principal Component Analysis–Based Feature Recognition Technology for Marine Plankton Images in IOT Systems. J Test Eval. 2024;52:1728-1737.

[15] Zhang Z, Ma L, Liu M, Chen Y, Zhao N. Adversarial Attacking and Defensing Modulation Recognition With Deep Learning in Cognitive-Radio-Enabled IOT. IEEE Internet Things J. 2024;11:14949-14962.

[16] Liftawi SM, Yousef IA, Kaied MW. An Accurate Classification for Human Sport Activity Recognition From Sensor Data Using Hybrid Machine Learning Models.J Adv Res Appl Sci Eng Technol. 2025;52:68-88.

[17] Yan Q, Wei Z, Lin Z, Kang X, Zhang W, et al. Apart and a Part: Overlapped Vibration Recognition for Distributed Optical Fiber Sensing Based on Deep Learning Separation. Opt Laser Technol. 2025;182:112083.

[18] Zhuravlev YI, Ryazanov VV, Ryazanov VV, Aslanyan LH, Sahakyan HA. Comparison of Different Dichotomous Classification Algorithms. Pattern Recognition and Image Analysis. 2020;30:303-314.

[19] Zhuravlev YI, Sen'ko OV, Bondarenko NN, Ryazanov VV, Dokukin AA, et al. A Method for Predicting Rare Events by Multidimensional Time Series With the Use of Collective Methods. Pattern Recognit Image Anal. 2019;29:763-768.

[20] Saymanov I. Logical Automatic Implementation of Steganographic Coding Algorithms. J Math Mech Comput Sci. 2024;121:122-131.

[21] Kabulov A, Normatov I, Saymanov I, Baizhumanov A. On the Completeness of Classes of Correcting Functions of Heuristic Algorithms. Az J Math. 2025;15.

[22] Kabulov AV, Normatov IH, Ashurov AO. Computational Methods of Minimization of Multiple Functions. J Phys Conf S. 2019;1260:10200.

[23] Kabulov A, Yarashov I, Otakhonov A. Algorithmic Analysis of the System Based on the Functioning Table and Information Security. In IEEE international IOT, electronics and mechatronics conference (IEMTRONICS). IEEE. 2022:1-5.

[24] Kabulov A, Saymanov I, Yarashov I, Karimov A. Using Algorithmic Modeling to Control User Access Based on Functioning Table. In IEEE international IOT, electronics and mechatronics conference (IEMTRONICS). IEEE. 2022:1-5.

[25] Kabulov A, Saymanov I, Yarashov I, Muxammadiev F. Algorithmic Method of Security of the Internet of Things Based on Steganographic Coding. In IEEE International IOT Electronics and Mechatronics Conference (IEMTRONICS). IEEE. 2021:1-5.

[26] Afanasieva TV, Platov PV, Medvedeva AI. Recommender Algorithm for Supporting Self-Management of CVD Risk Factors in an Adult Population at Home. Adv Artif Intell Mach Learn. 2024;4:2434-2451.

[27] Afanasieva TV, Platov PV, Komolov AV, Kuzlyakin AV. Leveraging ChatGPT and Long Short-Term Memory in Recommender Algorithm for Self-Management of Cardiovascular Risk Factors. Mathematics. 2024;12:2582.

[28] Yan Q, Wei Z, Lin Z, Kang X, Zhang W, et al. Apart and a Part: Overlapped Vibration Recognition for Distributed Optical Fiber Sensing Based on Deep Learning Separation. Opt Laser Technol. 2025;182:112083.

[29] Dubey A, Gantala T, Ray A, Prabhakar A, Rajagopal P. Quantum Machine Learning for Recognition of Defects in Ultrasonic Imaging. NDT & E Int. 2025;150:103262.

[30] Liu J, Zhang H. Fast Implementation of Object Detection Algorithm Based on Homomorphic Model Transformation. Neurocomputing. 2024;577:127313.

[31] Ali EH, Jaber HA, Kadhim NN. New Algorithm for Localization of Iris Recognition Using Deep Learning Neural Networks. Indonesian J Electr Eng Comput Sci. 2023;29:110-119.