UDC 004.85:519.172:519.816 **doi: 10.32620/reks.2025.4.10**

Igor SHELEHOV[1, 2], Dmytro PRYLEPA[2], Dmytro OLEFIRENKO[1], Roman KRYTSKYI[2]

[1] ***Sumy National Agrarian University, Sumy, Ukraine***
[2] ***Sumy State University, Sumy, Ukraine***

INFORMATION-EXTREME IDENTIFICATION OF UNMANNED AERIAL VEHICLES

*This research **aims** to detect and identify unmanned aerial vehicles (UAVs) by analyzing the network traffic they transmit to their ground control station. The relevance of this topic arises from the need to develop highly efficient UAV identification systems, given their widespread use across the military, civilian, and commercial sectors. Effective solutions for detecting, identifying, and classifying these devices are required. This study **aims** to develop models and methods that enable machine-learning-based UAV identification systems by analyzing incoming and outgoing data traffic using an extremely intelligent information technology. A methodology is proposed for applying extreme information technology to UAV identification. This methodology involves employing pattern recognition techniques and designing intelligent information systems. The scientific novelty lies in introducing an approach to modeling an intelligent system capable of learning to identify UAVs based on traffic characteristics analysis. **The research methodology** includes the following steps: (1) forming a training dataset based on UAV traffic parameters, (2) building a UAV identification system using an information-extreme approach, and (3) training the system under standard operating conditions of digital radio communication channels used by UAVs. **The results** demonstrate that the proposed intelligent information system provides high UAV identification accuracy. Testing achieved an average identification accuracy of 86%. **Conclusions**. The proposed UAV identification system is based on an innovative approach to network traffic analysis using information-extreme intelligent technology. The results confirm its effectiveness for identification tasks under standard regulated traffic characteristics. The obtained results have practical significance for developing monitoring and protection systems in various fields against potential threats associated with UAV usage*.

Keywords: *unmanned aerial vehicles; information-extreme machine learning; information criterion; functional-categorical model; traffic analysis; container of the recognition class.*

1. Introduction

1.1 Motivation

As UAVs become increasingly accessible, their use spans a wide range of fields, including commercial, scientific, military, and civilian sectors [1]. Due to the diversity of UAV applications, ensuring safety, which includes effective detection and identification of these devices, is an important aspect.

The relevance of this issue is determined by several factors. First, the growing availability of UAV technologies and their integration into various civilian and military systems create new threats to national security, citizens' privacy, and critical infrastructure stability [2], which amplifies the need for developing specialized systems for UAV rapid detection and identification. Second, although evolving, existing methods of UAV recognition and identification still face limitations in terms of accuracy, efficiency under challenging weather conditions, and adaptability to new types of UAVs [3].

In the scientific and practical context, the problem of UAV detection and identification is multidisciplinary, as it is related not only to engineering aspects but also to the application of artificial intelligence technology, signal processing, information theory, and other fields [4]. Meanwhile, the research focus is on methods for designing radar, optical, and acoustic detection systems for UAVs [5, 6]. However, a significant number of unsolved problems remain, such as minimizing identification errors and adapting to new UAV technologies that use visibility reduction and radar jamming techniques. This study proposes a set of so-called information-extreme intelligent models and machine learning methods that help overcome these limitations and enhance the reliability and speed of UAV identification.

1.2 State of the Art

State of the art UAV detection technologies include radar systems, optical devices, acoustic sensors, and radio frequency signal analysis methods. However, all these approaches have significant drawbacks. For example, radar systems may be ineffective when dealing with small, low-speed UAVs due to their low radar cross-section [5]. Optical methods depend on lighting and visibility conditions, which limits their effectiveness in adverse weather conditions [6]. Acoustic sensors are vulnerable

Creative Commons Attribution NonCommercial 4.0 International

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

to environmental noise pollution [7], and radio frequency spectrum analysis can become challenging when multiple signal sources are simultaneously monitored or in the presence of high levels of radio interference [8].

A number of modern works propose combining several sensor approaches, specifically the integration of optical, radar, and acoustic channels, which allows for increased UAV detection reliability under interference conditions [9, 10]. Multisensory data processing based on deep neural networks provides improved classification accuracy even with the partial absence of signals [11].

In this context, methods based on analyzing the data traffic transmitted between UAVs and their ground control stations open up new possibilities. Monitoring signal characteristics, such as radio frequency parameters, data transmission protocol patterns, and command control signatures, enables UAV identification even in the absence of direct visual contact or radar reflection [12].

Work [13] examined a UAV detection system model that combines network traffic analysis with visual information, which makes it possible to increase detection system reliability and response time. Another study [14] demonstrated the capabilities of adaptive data fusion in hybrid architectures, which use machine learning to optimize real-time identification processes.

The global scientific community is paying increasing attention to the use of machine learning methods for analyzing UAV data traffic. Convolutional neural networks (CNNs) can effectively classify signals in real time [15, 16]. For instance, the works [17, 18] proposed the use of deep neural networks to analyze the radio frequency spectrum, enabling UAV identification even under intense radio interference conditions. In [19], a system was developed to analyze Wi-Fi traffic that accounts for the unique signatures of UAVs during data transmission, while [20] explored UAV control command traffic, employing machine learning models to detect patterns specific to UAVs.

Recent research indicates the effectiveness of using deep neural architectures for recognizing low-visibility objects in aerial photographs and Earth remote sensing data, which is also relevant for UAV identification [21]. Specifically, [22] demonstrated that YOLOv8 and Swin-Transformer algorithms provide over 95% accuracy in multiclass drone identification, while [23] showed that using attention mechanisms improves performance when classifying micro-UAVs under complex lighting conditions.

Despite significant progress, most modern methods have certain limitations. The high computational complexity of machine learning algorithms often makes their real-time implementation impossible [24]. Moreover, many approaches are narrowly specialized and focus on a specific type of data transmission protocol or UAV type. Analyzing the radio frequency spectrum can be challenging in complex multi-platform environments, especially when multiple devices operate simultaneously [25].

The shortcomings of these approaches can be addressed using information-extreme intelligent technology (IEI technology). This approach ensures high functional efficiency in UAV traffic processing by leveraging its standard statistical characteristics [26]. Consequently, it provides high UAV identification accuracy even under challenging conditions, such as high noise levels or a crowded spectrum [27]. Furthermore, IEI technology reduces computational costs during machine learning and the application of the resulting UAV identification decision rules [28]. This opens up opportunities to develop real-time-operating efficient monitoring systems, which is crucial for maintaining security despite growing UAV-related threats.

1.3. Objectives and approaches

This research aims to develop new approaches to UAV identification based on the analysis of data traffic using IEI technology. This study aims to adapt the models and methods of the technology to ensure high UAV identification accuracy in a multi-platform environment with spectral noise and limited computational resources.

IEI technology can address a range of challenges associated with UAV traffic analysis by optimizing the identification system's genotypic and phenotypic parameters. A key feature of this approach is its ability to minimize information loss during signal processing and adapt to changing environmental conditions, such as interference or variations in data transmission protocols.

The following tasks are being addressed within the framework of this study:

1. Analyzing existing approaches to UAV identification and identifying their limitations in terms of accuracy, adaptability, and computational efficiency.
2. Developing an IEI-based machine learning model for UAV identification by analyzing their data traffic.
3. Developing methods for optimizing machine learning's genotypic and phenotypic parameters.
4. Experiments to evaluate the accuracy, robustness, and effectiveness of the proposed approaches under real-world conditions.

The results of this study are expected to contribute to the development of a highly accurate UAV identification system that is resistant to interference and capable of operating in real-time conditions.

The structure of the article includes several main sections. Section 2 presents the formalized information synthesis problem for the UAV identification system based on network traffic analysis. The key stages of training the decision support system (DSS) and optimizing its parameters are discussed. The system's categorical model is also described, covering the structure of sets and operators used to improve the learning and identification processes. Section 3 presents the experimental results of the proposed UAV identification model and training method. Section 4 discusses the research results in detail, which also develops the main conclusions and outlines future research directions.

2. Formalization of the proposed approach

2.1. Basic and enhanced EIT approach on the learning stage

We consider the formalized formulation of the problem of information synthesis for a UAV identification system based on network traffic analysis. The core component of such a system is a DSS that can learn and is built using IEI technology. Let's assume an alphabet $\{X_m^o \mid m = \overline{1,M}\}$ of recognition classes that characterize different types of UAVs, and a training matrix with statistical characteristics whose values are formed based on the analysis of incoming and outgoing network traffic $\| y_{m,i}^{(j)} \|, i = \overline{1,N}, j = \overline{1,n}$, where N and n represent the number of recognition features and traffic characteristic realizations, respectively. In this case, the row of the matrix $\{y_{m,i}^{(j)} \mid i = \overline{1,N}\}$ defines j-th realization of traffic, and the column $\{y_{m,i}^{(j)} \mid j = \overline{1,n}\}$ corresponds to a training sample of values for the i-th feature, which is key for UAV identification. A known structured vector of parameters for training the UAV identification system is as follows:

$$g =< x_m, d_m, \delta >, \tag{1}$$

where the genotypic parameters: x_m – a reference (averaged) vector-realization of network traffic parameters, the peak of which defines the geometric center of the class container X_m^o; d_m – the radius of the class container X_m^o, which is restored in the radial basis of the recognition feature space; and the phenotypic parameters: δ – parameters of the symmetric field for the control limits on recognition features.

At the machine learning stage of the DSS for UAV identification, the vector coordinates g must be optimized by searching for the global maximum of the information criterion of functional efficiency (CFE), averaged over the alphabet of recognition classes, used for optimizing the genotypic and phenotypic parameters:

$$\overline{E} = \frac{1}{M} \sum_{m=1}^{M} \max_{G_E} E_m , \tag{2}$$

where E_m represent the information CFE calculated during training for the current value of the class container's X_m^o hyper-spherical radius; G_E is the working (acceptable) area for defining the CFE function.

2.2. Categorical model of the DSSD

Because the UAV identification process is complex and variable, we consider the learning system's mathematical categorical model for UAV identification as a diagram of mappings with corresponding set operators used during information-extreme learning [29, 30]. The DSS input mathematical description is presented as a set structure

$$\Delta_B =< G, T, Z, \Omega, Y, X; P, f_1, f_2 >,$$

where G is the set of input network traffic factors; T is the set of time moments that characterize the data transmission moments; Ω is the feature recognition space; Z is the space of possible types of unmanned aerial vehicles; Y is the sample set (input training matrix) obtained after the initial traffic processing; P is the preprocessing operator for network traffic, which calculates the values of key traffic features, such as frequency, volume, and packet structure; $f_1 : G \times T \times \Omega \times Z \to Y$ is the traffic processing operator (forming the sample set Y at the input of the DSS); the operator f_2 transforms the input Euclidean training matrix Y into a binary matrix X.

Figure 1 shows the functional categorical model of the information-extreme machine learning for the UAV identification system in the form of a set mapping diagram or oriented graph.

In this model, the edges are operators that regulate the mapping of term sets involved in the process of extreme machine learning. As shown in Figure 1, the term set *E* has elements that are calculated at each step of machine learning according to the principle of full composition for the general optimization contours of the training parameters. The operator $r : E \to \tilde{\Re}^{|M|}$ at each learning step transforms into the radial basis of the binary

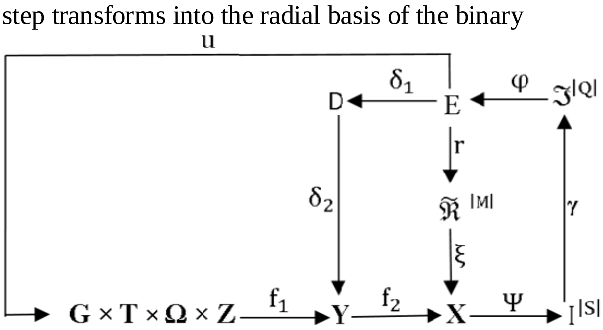

Fig. 1. Set Mapping Diagram of the UAV Identification System [26, 27]

 ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

feature space, where the recognition container classes form the classification $\tilde{\Re}^{|M|}$. The operator ξ maps the partition $\tilde{\Re}^{|M|}$ of the binary feature vectors of recognition classes $\{X_m^o\}$. The further operator $\psi: X \to I^{|C|}$ checks the primary statistical hypothesis $\gamma_1 : x_n^{(j)} \in X_m^o$. The operator γ defines the set of accurate characteristics $\Im^{|Q|}$, where $Q = C^2$, and the operator φ calculates the set E of values of the information optimization criterion, which is a functional of the accurate characteristics. Thus, the inner contour of operators (ψ, γ, φ, r, ξ) regulates the optimization of the system's genotypic parameters. The optimization contour of the control limits is closed through the term set D, whose elements are the control limit values for recognition features, and the operator u governs the machine learning process. Thus, the outer contour of operators regulates the optimization of the system's phenotypic parameters.

2.3. Algorithms

According to the categorical model in Figure 1, information-extreme machine learning for the DSS is performed through a multi-cycle iterative procedure, which involves searching for the global maximum of the information CFE within the working area defined by its function. The inner optimization contour is implemented as a basic learning algorithm, where the radius of the hyperspherical classifier is the optimized parameter of the functioning:

$$d_m^* = \arg \max_{G_E \cap \{d\}} E_m, \tag{3}$$

where $\{d\}$ represent the set of radius values for the class container X_m^o, restored in the recognition feature space's radial basis.

The outer loop of operators is implemented as an optimization algorithm for the control limits system δ on recognition features:

$$\delta^* = \arg \max_{G_\delta} \left(\frac{1}{M} \sum_{m=1}^{M} \max_{G_E} E_m \right), \tag{4}$$

where G_δ is the range of allowable values for the recognition feature control limit system.

Thus, at each step of the algorithm for optimizing phenotypic parameters, genotypic parameters are optimized.

The Kullback information measure [26, 30] can be used as the CFE for machine learning of the UAV identification system, which for equally probable two-alternative decisions has the form:

$$E_m^{(k)} = 0,5 \log_2 \left(\frac{D_1^{(k)} + D_2^{(k)} + 10^{-r}}{\alpha^{(k)} + \beta^{(k)} + 10^{-r}} \right) * \\ * \left[\left(D_1^{(k)} + D_2^{(k)} \right) - \left(\alpha^{(k)} + \beta^{(k)} \right) \right], \tag{5}$$

where $D_1^{(k)}$, $D_2^{(k)}$ are the first and second reliabilities calculated at the k-th step of the training; $\alpha^{(k)}$, $\beta^{(k)}$ are the first and second type errors; 10^{-r} is a sufficiently small number to avoid division by zero.

Within the framework of IEI technology, the process of restoring the class-separation hypersurfaces for UAVs is performed on the radial basis of the binary feature space obtained from the analysis of network traffic. The closed separating hyper-surface, whose geometric center is determined using special algorithms, is commonly referred to as the corresponding recognition class's container. The geometric shape of these containers determines the type of decision rules constructed during machine learning.

Thus, the optimization of the learning parameters for the UAV identification system is based on a multi-level iterative procedure for searching the global maximum of the information criterion (5) in the working area. The optimization of phenotypic parameters is performed at the outer level, while the optimization of genotypic parameters is performed at the inner level. The following main functions are performed:

– calculation of the information criterion (5) at each training stage;

– search for the global maximum of the information criterion within the working area;

– determination of the optimal parameter values for each recognition class separately or alphabetically.

This ensures the achievement of the maximum identification accuracy of UAVs based on the statistical characteristics of their network traffic without the detailed analysis of transmitted packets.

The decision rules formed during the information-extreme machine learning process are presented in the form of a system of predicate expressions:

$$\begin{cases} \forall X_m^o \ \forall x^{(j)} \left[\begin{array}{l} (\mu_m \geq 0) \& \left(\mu_m = \max\limits_{k=1,M} \{\mu_k\} \right) \\ \to \left(x^{(j)} \in X_m^o \right) \end{array} \right] \\ \forall X_m^o \ \forall x^{(j)} \left[\begin{array}{l} (\mu_m < 0) \\ \to \left(x^{(j)} \notin X_m^o \right) \end{array} \right] \end{cases} \tag{6}$$

where $x^{(j)}$ is the vector to be recognized; μ_m is the function that defines the membership of the vector $x^{(j)}$ to the container of the recognition class X_m^0.

The value of μ_m is determined by the following formula:

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

where x_m^*, d_m^* are the parameters of the optimal recognition class container X_m^0 obtained during machine learning.

Thus, the procedure for applying the constructed decision rules allows for real-time UAV identification and the detection of unknown UAV classes with the possibility of further expanding the alphabet of classes and re-training the intelligent system.

2.4. Structural functional diagram

The UAV identification system structure (Fig. 2) is based on the principles of IEI technology. All system blocks can be divided into three functional groups: analysis-synthesis, decision-making, and registration. The system adapts its operation to two main modes: learning and evaluation, which are determined by the operator through the interface. When the learning mode is selected, the system activates the blocks of the analysis-synthesis group, namely:

– Primary Information Processing Block (PIPB): performs intelligent analysis of input data. At this stage, the DSS parameters are optimized using information-extremum machine learning methods.

– Container Formation Block (CFB): implements the information-extremum machine learning algorithm, optimizing the geometric parameters of the recognition classes. This corresponds to the set mapping in the identification system.

– Machine Learning Parameter Optimization Block (MLPOB): determines the optimal operating parameters of the DSS. This block constructs the optimal values of the containers through a multi-cycle iterative procedure aimed at finding the global maximum of the averaged value of the functional efficiency (FE).

An operational database (ODB) is created at the initial stage of the system's operation, which is a dynamic copy of the main database (DB). The ODB provides the other blocks with the necessary data for their correct functioning.

The results of information-extremum machine learning, namely, the optimal operating parameters, are stored in the knowledge base. In the decision-making mode, these parameters are transferred to the Functional Efficiency Calculation Block (FECB). The FECB, which receives the results of the current UAV identification from the ODB, belongs to the decision-making group. The results registration group includes the DB, ODB, knowledge base, and the Output Block. The results of the FECB's work in the analysis-synthesis mode are displayed to the operator through the system interface in the form of values, tables, or graphs that show the performance indicators' dependence on the factors that influence the identification process. The operator can view and edit the ODB through the system interface.

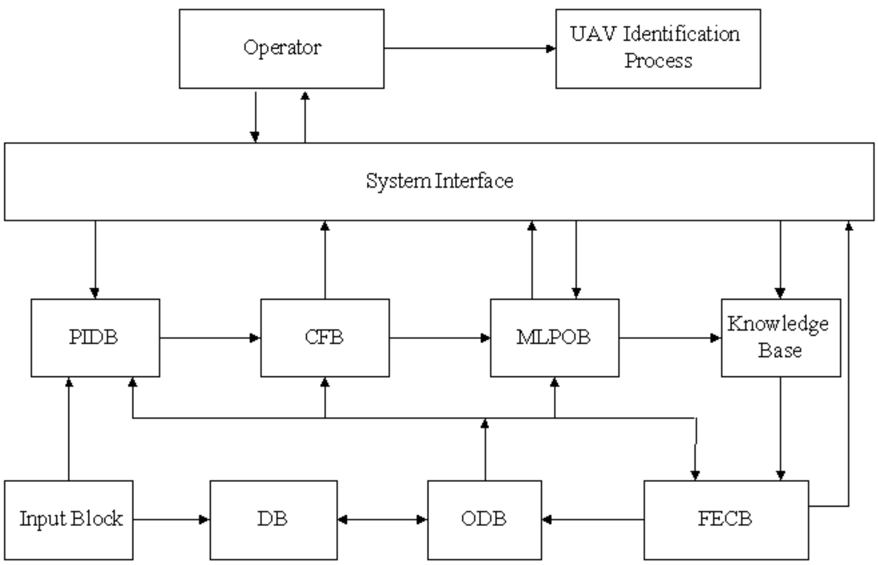

Fig. 2. Functional diagram structure of the UAV identification system

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

This structure ensures the identification process's flexibility and effectiveness, allowing the system to adapt and improve its performance over time.

3. Experiments and Results

The formation of the input mathematical description for an intelligent system capable of learning to identify UAVs based on the analysis of their network traffic was performed using data from the Machine Learning Repository at the Center for Machine Learning and Intelligent Systems at the University of California, Irvine (USA) [31]. The implementation of the machine learning algorithm according to procedure (3) was based on the input training matrix, which was created for three recognition classes: X_1^o – network traffic analyzed includes data corresponding to the characteristics of the Parrot Bebop UAV; X_2^o – data corresponding to the characteristics of the DBPower UDI UAV; X_3^o – data for the DJI Spark UAV. To formulate the input mathematical description of the intelligent system, the "Unmanned Aerial Vehicle (UAV) Intrusion Detection" dataset from the repository of the Center for Machine Learning and Intelligent Systems at the University of California, Irvine (USA) [31] was utilized. The training matrix was constructed from the values of 54 statistical traffic parameters, including packet volume, average latency, transmission frequency, and other network activity characteristics.

A key advantage is that the used attribute set is universal and independent of the specific UAV type or manufacturer, as it is based on most unmanned control systems' generalized statistical traffic parameters characteristic. This approach enables the future adaptation of the technology to other UAV types without requiring significant modification of the mathematical model. The relevant section of the data repository provides a comprehensive list and description of the features, ensuring the reproducibility and validity of the parameters used.

The number of realizations for each class was 235, where each column of the matrix corresponded to the value of a separate indicator, and the rows contained realizations of these indicators for each UAV type. Since the statistical characteristics of traffic each have their own area of definition, reducing their values to a common (consolidated) scale using a transformation is advisable:

$$y_{m,i}^{(j)} = W \frac{y_{m,i}^{(j)} - \min\limits_{\substack{m=\overline{1,M} \\ j=\overline{1,n}}} y_{m,i}^{(j)}}{\max\limits_{\substack{m=\overline{1,M} \\ j=\overline{1,n}}} y_{m,i}^{(j)} - \min\limits_{\substack{m=\overline{1,M} \\ j=\overline{1,n}}} y_{m,i}^{(j)}},$$

where W is the indicator's maximum value on the consolidated scale at the corresponding minimum value of 0.

An information-extremal machine learning algorithm has been implemented for the given alphabet of recognition classes, which ensures parallel optimization of the system of control tolerances reduced to a common scale (CSCT), where W = 250.

Figure 3 shows the graph of the dependence of the averaged Kullback information measure (5) on the parameter δ, which sets the width of the CSCT field for all recognition features simultaneously.

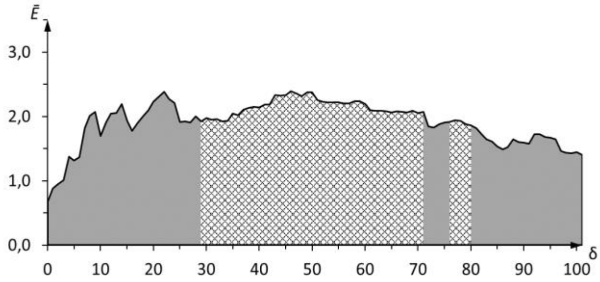

Fig. 3. Graph of the dependence of the averaged CFE on the parameters of the control tolerance system on the consolidated scale for recognition features

In Figure 3 and in the text, the shaded part of the graph is designated as the working (permissible) area for defining the function (4), in which the values of the first and second type errors are smaller than the values of the first and second confidence levels, respectively [29, 30]. Analysis of Fig. 3 shows that the maximum value of the averaged CFE was reached at step 46 and amounted to 2.388, which ensures a clear distinction between recognition classes.

The optimal radii of the recognition class containers for UAVs were determined within the internal cycle of the algorithm (3) to construct decision rules. Figure 4 shows the results of the optimization of geometric parameters for this control tolerance system.

The analysis of the optimization results (Fig. 4) shows that the optimal parameters for the class container X_1^o are radius d_1 = 10 with an inter-center distance d_c = 12, for the class X_2^o radius d_2 = 8 with d_c = 12, and for the class X_3^o radius d_3 = 8 with d_c = 14. These container parameters correspond to the following values of CFE and accuracy characteristics: for the class X_1^o: E = 2.130 (D_1 = 0.84; β = 0.04); for the class X_2^o: E = 1.576 (D_1 = 0.71; β = 0); for the class X_3^o: E = 3.458 (D_1 = 0.94; β = 0).

The results of testing the UAV identification system, built based on decision rules, showed that the overall probability of correct classification is 0.83. An information-extremal machine learning algorithm has been implemented to improve accuracy, which performs sequential optimization of control tolerances. In this approach, the initial control tolerance values were obtained during parallel optimization. Figure 5 shows the dynamics of the averaged information criterion value during the parallel-sequential tolerance optimization.

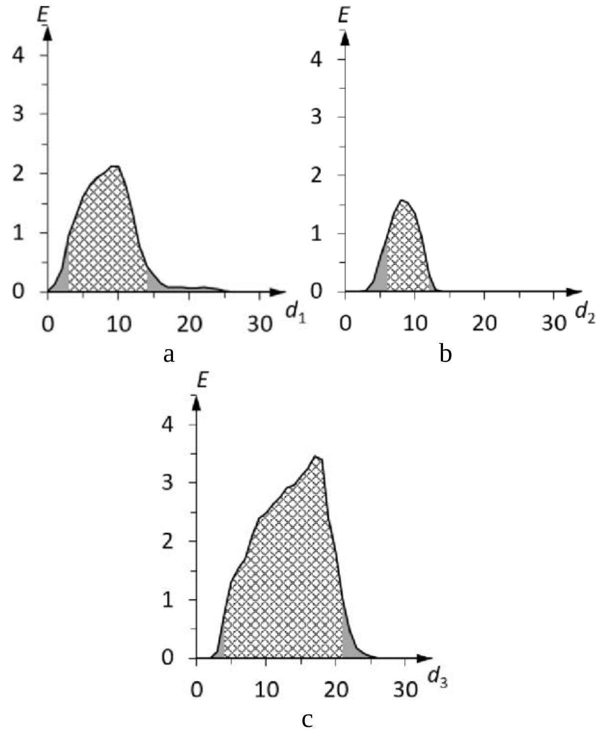

Fig. 4. Graph of the dependence of CFE on the geometric parameters of the class containers:
a) class x_1^o – «Parrot Bebop»,
b) class x_2^o – «DBPower UDI»,
c) class x_3^o – «DJI Spark»

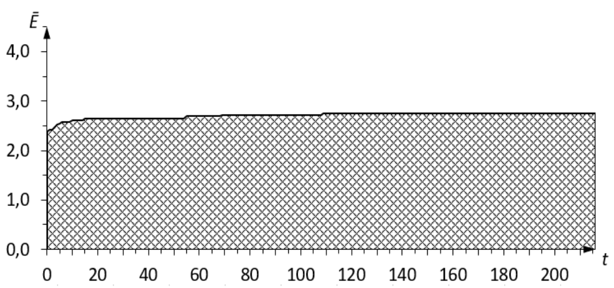

Fig. 5. Graph of dependence of the averaged CFE during the sequential optimization of the control tolerances

Figure 5 shows that the maximum value of the averaged information CFE is achieved at the 270th iteration and equals 2.751, which improves the performance compared to the value obtained through parallel optimization. Figure 6 shows the results of optimizing the geometric parameters for this control tolerance system.

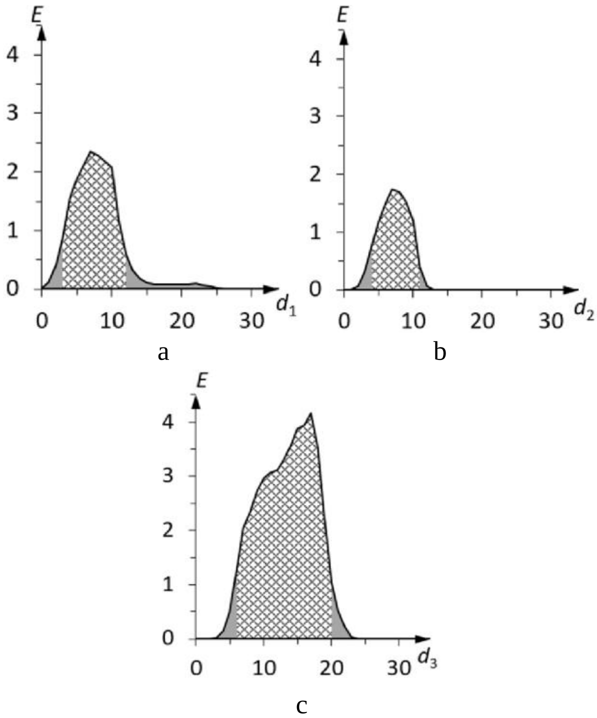

Fig. 6. Graph of CFE dependence on the geometric parameters of the class containers:
a) class x_1^o – «Parrot Bebop»,
b) class x_2^o – «DBPower UDI»,
c) class x_3^o – «DJI Spark»

The analysis of the optimization results (Figure 6) shows that the optimal container parameters for class x_1^o are a radius of d_1=7 with a center-to-center distance d_c=11, for class x_2^o a radius of d_2=7 with d_c=11, and for class x_3^o a radius of d_3=17 with d_c=20. The corresponding values of the CFE and accuracy characteristics for these container parameters are as follows: for class x_1^o: E = 2.354 (D_1=0.84; β = 0.01); for class x_2^o: E = 1.744 (D_1 = 0,74; β = 0); for class x_3^o: E = 4.156 (D_1 = 1.00; β = 0.01). As previously noted, the results of testing the UAV identification system, built on the basis of decision rules, showed that the overall probability of correct classification was 0.83. This figure increased to 0.86 after applying the sequential optimization algorithm for control tolerances, indicating an improvement in classification accuracy and the effectiveness of the proposed approach.

Within the information-extreme approach applied in this study, classification performance is evaluated not by a traditional "point" metric, but by Kullback's information measure (E_m) [26, 30]. This is a generalized recognition quality function that integrally accounts for the balance between reliabilities (D_1 – analogous to True Positive, D_2 – analogous to False Positive) and Type I (α – analogous to True Negative) and Type II (β – analogous to False Negative) errors. Unlike static metrics (e.g.,

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

accuracy, F_1 -score), the E_m value is calculated at each iterative optimization step and serves as the objective criterion for the machine learning of the system.

Thus, the graphical dependencies presented in Section 3 (Figs. 3-6) are not "point estimations" or "partial" assessments of accuracy. Instead, they illustrate the dynamics (evolution) of the learning process—the search for the global maximum of the CFE E_m during the optimization of parameters (container radii d_m and control tolerances δ). The growth of the E_m curve in these plots demonstrates how the system progressively improves its decision consistency, which is a significantly more comprehensive characteristic of effectiveness than a single summary evaluation.

In light of this, the proposed set of methods and models ensures the formation of highly accurate decision rules for the UAV identification system based on the network traffic analysis in UAV monitoring and control tasks under real operational conditions.

4. Discussion

The results of this study indicate that the parallel-sequential optimization of the control tolerance system provides an overall classification accuracy of 86%. The obtained accuracy is competitive compared with existing UAV identification systems based on radio frequency signal analysis and optical methods, which typically demonstrate accuracy in the range of 75-90%. It is advisable to consider applying base-class selection algorithms [27] to further enhance recognition accuracy, which would allow the control tolerances to be more effectively adapted to the specific characteristics of each class.

An important advantage of the proposed approach is its resilience to spectral interference and variability in data transmission protocols, which frequently occur in real-world UAV operational environments. The established decision rules enable real-time execution of the examination stage, which is important for the UAV identification system's practical application. However, as the number of classes increases, more complex algorithms are required. One promising direction is the introduction of a hierarchical approach, which involves organizing recognition classes into strata, each consisting of a group of the closest neighboring classes [32, 33].

A comparative analysis with traditional machine learning methods shows that the information-extreme approach offers better adaptability to changing operational conditions and lower computational resource requirements. Although the results of implementing hierarchical algorithms are not yet available, their use may improve recognition accuracy by optimizing tolerances for each stratum individually. Although constructing such a hierarchical structure may take more time, it offers the possibility of more efficient system operation as the number of classes grows.

The limitation of the current study is that testing was conducted only on a controlled dataset. Further validation on real-world data from various geographic regions and diverse operational conditions is necessary to confirm the approach's universality.

Thus, the proposed approach, based on parallel-sequential optimization, demonstrates high functional efficiency and accuracy in UAV identification tasks. Further research will focus on implementing an enhanced set of IEIT models and methods to improve classification accuracy and system adaptability.

5. Conclusions

The proposed models and methods of information-extreme machine learning for UAV identification systems are based on the analysis of network traffic transmitted to the ground control station. The implementation of this approach has enabled the system to achieve high functional efficiency, ensuring an 86% accuracy rate in classifying UAV types. The system has significantly lower computational costs than other methods, making it suitable for use in real-time environments, where rapid decision-making is crucial.

The main scientific contributions of this study are: the development of an adaptive methodology for applying information-extreme technology to UAV network traffic analysis, the formalization of the information synthesis problem for a UAV identification system, and the experimental validation of the effectiveness of parallel-sequential optimization of control tolerances.

The optimal adjustment of classification parameters was an important factor in improving accuracy, which helped minimize the risk of erroneous decisions. Simultaneously, the effectiveness of parallel-sequential optimization, normalized to a common scale for the system of control tolerances on recognition features, was demonstrated. The practical significance of the results lies in the integration of the developed system into existing airspace monitoring complexes and counter-UAV threat systems.

Further research will focus on addressing the problem of adapting the system to the expansion of the alphabet of class quantities (including in the context of factorial cluster analysis). In particular, the implementation of a hierarchical approach is promising because it will allow the construction of multi-level data structures and the configuration of the CSCT for each level. Additionally, the application of algorithms for selecting the base class is considered promising because it will enhance the classification accuracy and the formation of error-free decision rules based on the training matrix under conditions of varying traffic characteristics. The application of factorial cluster analysis methods opens opportunities for the automatic detection of new UAV types and for adapting the system to the evolution of UAV technologies without the need for complete system retraining.

Contribution of authors: development of conceptual provisions and methodology of research, formulation of conclusions – **Igor Shelehov, Roman Krytskyi**; Review and analysis of references; development of software for modeling – **Dmytro Olefirenko, Dmytro Prylepa**; development of mathematical models, analysis of research results – **Dmytro Prylepa, Igor Shelehov**.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

This study was conducted without financial support.

Data Availability

The manuscript has associated data in a data repository: Center for Machine Learning and Intelligent Systems, University of California [31], Irvine (USA) and can be found here https://archive.ics.uci.edu/ml/datasets/Unmanned+Aerial+Vehcle+%28UAV%29+Intrusion+Detection, accessed on April 11, 2020.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods while creating the presented work.

Acknowledgments

The authors thank the Ministry of Education and Science of Ukraine for providing sup-port to the Laboratory of Intellectual Systems within the framework of research project No. 0124U000548 "Information Technology for Ensuring the Resilience of the Intelligent Onboard System of Small-Sized Aircraft" (2024–2026).

All authors have read and agreed with the published version of the manuscript.

References

1. Moskalenko, V., Korobov, A., & Moskalenko, Y. Object detection with affordable robustness for UAV aerial imagery: model and providing method. *Radioelectronic and Computer Systems*, 2024, iss. 3, pp. 55-66. DOI: 10.32620/reks.2024.3.04.

2. Fesenko, H., Illiashenko, O., Kharchenko, V., Kliushnikov, I., Morozova, O., Sachenko, A., & Skorobohatko, S. Flying Sensor and Edge Network-Based Advanced Air Mobility Systems: Reliability Analysis and Applications for Urban Monitoring. *Drones*, 2023, vol. 7, iss. 7, article no. 409. DOI: 10.3390/drones7070409.

3. Tsekhmystro, R., Rubel, O., Prysiazhnik, O., & Lukin, V. *Impact of Distortions in UAV Images on Quality and Accuracy of Object Localization*. *Radioelectronic and Computer Systems*, 2024, iss. 4, pp. 59-67. DOI: 10.32620/reks.2024.4.05.

4. Vasilyeva, I., Lukin, V., Kharchenko, V. & Nereta, A. Combined processing of satellite and UAV data to increase the classification reliability. *IntelITSIS'2023: 4th International Workshop on Intelligent Information Technologies and Systems of Information Security*, 2023, pp 539-552.

5. Jalil, H. H., Cao, Y., Li, S., Hu, Y., Wang, J., & Wang, S. Real-time Collaborative Intrusion Detection System in UAV Networks Using Deep Learning. *IEEE Internet of Things Journal*, 2024, vol. 11, iss. 20, pp. 33371-33391. DOI: 10.1109/JIOT.2024.3426511.

6. Zaman, F., Tahir, N., Yusoff, Y., Thamrin, N., & Hasmi, A. Human Detection from Drone using You Only Look Once (YOLOv5) for Search and Rescue Operation. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 2023, vol. 30, iss. 3, pp. 222-235. DOI: 10.37934/araset.30.3.222235.

7. Wang, S., Wang, J., Su, C., & Ma, X. Intelligent detection algorithm against UAVs' GPS spoofing attack. *2020 IEEE 26th International Conference on Parallel and Distributed Systems (ICPADS)*, Hong Kong, China, IEEE, 2020, pp. 382-389. DOI: 10.1109/ICPADS51040.2020.00058.

8. Arthur, M. P. Detecting signal spoofing and jamming attacks in UAV networks using a lightweight IDS. *2019 International Conference on Computer, Information and Telecommunication Systems (CITS)*, Beijing, China, IEEE, 2019, pp. 1-5. DOI: 10.1109/CITS.2019.8862148.

9. Rahman, M. H., Sejan, M. A. S., Aziz, M. A., Tabassum, R., Baik, J.-I., & Song, H.-K. A Comprehensive Survey of Unmanned Aerial Vehicles Detection and Classification Using Machine Learning Approach: Challenges, Solutions, and Future Directions. *Remote Sens.*, 2024, vol. 16, iss. 5, article no. 879. DOI: 10.3390/rs16050879.

10. Fang, A., Feng, S., Liang, B., & Jiang, J. Real-Time Detection of Unauthorized Unmanned Aerial Vehicles Using SEB-YOLOV8s. *Sensors*, 2024, vol. 24, iss. 12, article no. 3915. DOI: 10.3390/s24123915.

11. Gao, D., Tang, J., Li, H., Wang, B., Qiu, J., Chen, S., & Mei, X. A Novel Dataset and Detection Method for Unmanned Aerial Vehicles Using an Improved YOLOV9 Algorithm. *Sensors*, 2024, vol. 24, iss. 23, article no. 7512. DOI: 10.3390/s24237512.

12. Maurício, J., Domingues, I., & Bernardino, J. Comparing Vision Transformers and Convolutional Neural Networks for Image Classification: A Literature Review. *Applied Sciences*, 2023, vol. 13, iss. 9, article no. 5521. DOI: 10.3390/app13095521.

13. Wang, B., Li, Q., Mao, Q., Wang, J., Philip Chen, C. L., Shangguan, A., & Zhang, H. A Survey on Vision-Based Anti Unmanned Aerial Vehicles Methods.

Drones, 2024, vol. 8, iss. 9, article no. 518. DOI: 10.3390/drones8090518.

14. Guo, D., Qu, Y., Zhou, X., Sun, J., Yin, S., Lu, J., & Liu, F. Research on Automatic Tracking and Size Estimation Algorithm of "Low, Slow and Small" Targets Based on Gm-APD Single-Photon LIDAR. *Drones*, 2025, vol. 9, iss. 2, article no. 85. DOI: 10.3390/drones9020085.

15. Konert, A., & Balcerzak, T. Military Autonomous Drones (UAVs) – from fantasy to reality. Legal and Ethical Implications. *Transportation Research Procedia*, 2021, vol. 59, pp. 292-299. DOI: 10.1016/j.trpro.2021.11.121.

16. Almasri, M. Deep learning for RF-based drone detection and identification using Welch's method. *Proceedings of the 11th International Conference on Data Science, Technology and Applications*, France, 2021, pp. 208-214. DOI: 10.5220/0010530302080214.

17. Allahham, M. S., Khattab, T., & Mohamed, A. Deep learning for RF-based drone detection and identification: A multi-channel 1-D convolutional neural networks approach. *2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT)*, Doha, Qatar, IEEE, 2020, pp. 112-117. DOI: 10.1109/ICIoT48696.2020.9089657.

18. Vitali, E., Lokhmotov, A., & Palermo, G. Dynamic network selection for the object detection task: Why it matters and what we (didn't) achieve. *Embedded Computer Systems: Architectures, Modeling, and Simulation (SAMOS 2021)*, Springer, Cham, 2021, pp. 467-480. DOI: 10.1007/978-3-031-04580-6_31.

19. Geng, S., Wei, Z., Zhao, J., & Shen, F. Joint deployment and resource allocation for service provision in multi-UAV-assisted wireless networks. *IEEE Internet of Things Journal*, 2024, vol. 11, iss. 22, pp. 37269-37286. DOI: 10.1109/JIOT.2024.3443125.

20. Vanitha, N., & Ganapathi, P. Traffic Analysis of UAV Networks Using Enhanced Deep Feed Forward Neural Networks (EDFFNN). *Advances in Information Security, Privacy, and Ethics*, 2020, pp. 219-244. DOI: 10.4018/978-1-5225-9611-0.ch011.

21. Belwafi, K., Alkadi, R., Alameri, S. A., Hamadi, H. A., & Shoufan, A. Unmanned Aerial Vehicles' Remote Identification: A Tutorial and Survey. *IEEE Access*, 2022, vol. 10, pp. 87577-87601. DOI: 10.1109/ACCESS.2022.3199909.

22. Shi, Q., Hu, Y., Yang, T., Li, M., & Ding, D. Deep Learning Identification of Unmanned Aerial Vehicles with Hardware Implementation. *International Applied Computational Electromagnetics Society Symposium (ACES-China)*, 2023, pp. 1-3. DOI: 10.23919/ACES-China60289.2023.10249407.

23. Okkalı, E., Şolpan, Ş., & Küçük, K. Machine Learning-Based Detection of Unmanned Aerial Vehicles Using Radio Frequency Signals. *Innovations in Intelligent Systems and Applications Conference (ASYU)*, 2024, pp. 1-6. DOI: 10.1109/ASYU62119.2024.10757113.

24. McCoy, J., Rawal, A., Rawat, D. B., & Sadler, B. M. Ensemble Deep Learning for Sustainable Multimodal UAV Classification. *IEEE Transactions on Intelligent Transportation Systems*, 2023, vol. 24, iss. 12, pp. 15425-15434. DOI: 10.1109/TITS.2022.3170643.

25. Anwar, M. Z., Kaleem, Z., & Jamalipour, A. Machine Learning Inspired Sound-Based Amateur Drone Detection for Public Safety Applications. *IEEE Transactions on Vehicular Technology*, 2019, vol. 68, iss. 3, pp. 2526-2534. DOI: 10.1109/TVT.2019.2893615.

26. Dovbysh, A. S. *Osnovy proektuvannia intelektualnykh system: Navchalnyi posibnyk.* [Fundamentals of intelligent systems design: A study guide]. Sumy, Vydavnytstvo SumDU, 2009. 172 p. (In Ukrainian)

27. Dovbysh, A. S., Budnyk, M. M., Piatachenko, V. Yu., & Myronenko, M.I. Information-Extreme Machine Learning of On-Board Vehicle Recognition System. *Cybernetics and Systems Analysis*, 2020, vol. 56, iss. 4, pp 534-543. DOI:10.1007/s10559-020-00269-y.

28. Shelehov, I. V., Prylepa, D. V., Khibovska, Y. O., & Otroshcenko M. S. Machine learning decision support systems for adaptation of educational content to the labor market requirements. *Radio Electronics, Computer Science, Control*, 2023, vol. 1, pp. 62-72. DOI: 10.15588/1607-3274-2023-1-6.

29. Dovbysh, A. S., Shelehov, I. V., & Olefirenko, D. V. Optimization of control tolerances for recognition features in information-extremal methods of automatic classification. *Abstracts of IX International Scientific and Practical Conference «Research of young scientists: from idea generation to project implementation»*, Lyon, France, 2024, p. 228-235. Available at: https://eu-conf.com/en/events/research-of-young-scientists-from-idea-generation-to-project-implementation/ (accessed 12.02. 2025).

30. Shelehov, I., Prylepa, D., Khibovska, Y., & et al. Information-Extreme Machine Learning of an Ophthalmic Diagnostic System with a Hierarchical Class Structure. *Artificial Intelligence*, 2024, no. 3, pp. 114–125. DOI: 10.15407/jai2024.03.114.

31. *Center for Machine Learning and Intelligent Systems, University of California, Irvine. Unmanned Aerial Vehicle (UAV) Intrusion Detection* [Dataset]. Available at: https://archive.ics.uci.edu/ml/datasets/Unmanned+Aerial+Vehicle+%28UAV%29+Intrusion+Detection (accessed 04.11.2020).

32. Shelehov, I. V., Barchenko, N. L., Prylepa, D. V., & Bibyk, M. V. Information-extreme machine training system of functional diagnosis system with hierarchical data structure. *Radioelectronics, Informatics, Control*, 2022, vol. 2. pp. 189-200. DOI: 10.15588/1607-3274-2022-18.

33. Dovbysh, A. S., & Piatachenko, V. Y. Hierarchical clustering approach for information-extreme machine learning of hand brush prosthesis. *Proceedings of the 5th international conference on computational linguistics and intelligent systems*, Kharkiv, 2021, pp. 1706-1715. Available at: https://ceur-ws.org/Vol-2870/paper123.pdf. (15.03.2025).

Received 14.03.2025, Received in revised form 28.10.2025
Accepted date 17.11.2025, Published date 08.12.2025

ІНФОРМАЦІЙНО ЕКСТРЕМАЛЬНА ІДЕНТИФІКАЦІЇ БЕЗПІЛОТНИХ ЛІТАЛЬНИХ АПАРАТІВ

І. В. Шелехов, Д. В. Прилепа, Д. В. Олефіренко, Р. С. Крицький

Об'єктом дослідження є процес детектування та ідентифікації безпілотних літальних апаратів (БПЛА) шляхом аналізу мережевого трафіку, який передається ними на наземну станцію керування. Актуальність теми зумовлена необхідністю створення високоефективних систем ідентифікації БПЛА у зв'язку з їхнім широким використанням у військових, цивільних і комерційних сферах, що зумовлює потребу в ефективному вирішенні задач детектування, ідентифікації та класифікації таких пристроїв. **Метою** дослідження є розробка моделей і методів, які забезпечують машинне навчанні системи ідентифікації БПЛА на основі аналізу вхідного та вихідного трафіку даних за допомогою інформаційно-екстремальної інтелектуальної технології. Запропоновано методологію використання інформаційно-екстремальної технологій для ідентифікації БПЛА, яка включає застосування методів ідентифікації образів і проектування інформаційних інтелектуальних систем. Науковою новизною є впровадження підходу до моделювання інтелектуальної системи, здатної навчатися ідентифікації БПЛА на основі аналізу характеристик їх трафіку. **Методика** дослідження базується на розробці системи із застосуванням наступних етапів: (1) формування навчального набору даних із параметрів трафіку БПЛА, (2) побудова системи ідентифікації БПЛА із використанням інформаційно-екстремального підходу, (3) машинне навчання системи у стандартних режимах функціонування цифрових радіоканалів зв'язку БПЛА. **Результати** дослідження демонструють, що запропонована інтелектуальна інформаційна система здатна забезпечити високу точність ідентифікації БПЛА. У тестуванні було досягнуто середньої точності ідентифікації на рівні 86%. **Висновки**. Запропонована в роботі система ідентифікації БПЛА базується на інноваційному підході до аналізу мережевого трафіку за допомогою інформаційно-екстремальної інтелектуальної технології. Результати дослідження підтверджують її ефективність для задач ідентифікації в умовах стандартних регламентованих характеристик трафіку. Отримані результати мають практичне значення для створення систем моніторингу та захисту від потенційних загроз, пов'язаних із використанням БПЛА у різних сферах діяльності.

Ключові слова: безпілотні літальні апарати; інформаційно-екстремальне машинне навчання; інформаційний критерій; функціонально-категоріальна модель; аналіз трафіку; контейнер класу розпізнавання.

Шелехов Ігор Володимирович – канд. техн. наук, доц., доц. каф. кібернетики та інформатики, Сумський національний аграрний університет, Суми, Україна; доц. каф. комп'ютерних наук, Сумський державний університет, Суми, Україна.

Прилепа Дмитро Вікторович – канд. техн. наук, асист. каф. комп'ютерних наук, Сумський державний університет, Суми, Україна.

Олефіренко Дмитро Володимирович – здобувач каф. кібернетики та інформатики, Сумський національний аграрний університет, Суми, Україна.

Крицький Роман Сергійович – асп. каф. комп'ютерних наук, Сумський державний університет, Суми, Україна.

Igor Shelehov – PhD, Associate Professor at the Department of Cybernetics and Informatics Department of Sumy National Agrarian University, Sumy, Ukraine; PhD, Associate Professor at the Computer Science Department of Sumy State University, Sumy, Ukraine,
e-mail: i.shelehov@cs.sumdu.edu.ua, ORCID: 0000-0003-4304-7768, Scopus Author ID: 55537177800.

Dmytro Prylepa – PhD, Assistant at the Computer Sciences Department of Sumy State University, Sumy, Ukraine, e-mail: d.prylepa@cs.sumdu.edu.ua, ORCID: 0000-0002-4022-5496, Scopus Author ID: 57192820992.

Dmytro Olefirenko – Student of the Cybernetics and Informatics Department, Sumy National Agrarian University, Sumy, Ukraine, e-mail: dimaolefirenko67@gmail.com.

Roman Krytskyi – PhD Student of the Computer Science Department, Sumy State University, Sumy, Ukraine,
e-mail: itoktor@gmail.com, ORCID: 0000-0003-4878-5575.