ЦИФРОВІ ТЕХНОЛОГІЇ

UDC 004.94=111 DOI: https://doi.org/10.31617/zt.knute.2019(104)07

KRYVORUCHKO Olena
DSc (Engineering), Professor, Head of Department of Software Engineering and Cyber Security of Kyiv national university of trade and economics
19, Kyoto str., Kyiv, 02156, Ukraine
E-mail: kryvoruchko_ev@knute.edu.ua
ORCID: 0000-0002-7661-9227

KHOROLSKA Karyna
Server-side Developer, Softorino Inc.
Huntington Beach, California, USA
E-mail: karynakhorolska@gmail.com
ORCID: 0000-0003-3270-4494

CHUBAIEVSKYI Vitalii
PhD (Political Sciences), Associate Professor of Department of Software Engineering and Cyber Security of Kyiv national university of trade and economics
19, Kyoto str., Kyiv, 02156, Ukraine
E-mail: chubaievskyi_vi@knute.edu.ua
ORCID:0000-0001-8078-2652

USAGE OF NEURAL NETWORKS IN IMAGE RECOGNITION

This article focuses on the operation of the classification of blueprint parts. Classification characteristic is the main part of the designation of the part or product and their design documents, solving a number of topical tasks from creation of a single information language for automated systems to unification and standardization.

Keywords: neural network, object recognition, classification, domains.

Криворучко Е., Хорольская К., Чубаевский В. Использование нейронных сетей в распознавании изображений. *Рассмотрено функционирование и сформирована классификация элементарных объектов изображений. Классификационная характеристика является важной частью, которая решает ряд актуальных задач – от создания единого информационного языка для автоматизированных систем до унификации и стандартизации.*

Ключевые слова: нейронная сеть, объект распознавания, классификация, домены.

Background. Currently, various image recognition methods and systems based on them are actively developing, successfully solving such tasks as identifying fingerprints, corneas of the eye, analyzing aerospace images, monitoring information flows in a computer network, detecting forgeries, recognizing license plates, handwritten texts, scanned postal, latent, financial and accounting documents. Those methods of pattern recognition made it possible to solve complex tasks. In this regard, it is necessary to consider the possibility of applying these methods for automatic recognition building blueprints to generate a 3D model of the construction.

Analysis of recent research and publications. Along past decade there was few valuable publications in field of image recognition using neural networks. Most of them concern face recognition technologies or movement and movement prediction approaches. Nevertheless way back to 2016 was fundamental study of 3d object recognition and algorithms using neural networks by Luís A. Alexandre called «3D Object Recognition Using Convolutional Neural Networks with Transfer Learning Between Input Channels» [1]. Stating that current trend in processing image data is the use of convolutional neural networks (CNNs) that have consistently beat competition in most benchmark data sets. Luís aim was to investigate the possibility of transferring knowledge between CNNs when processing RGB-D data with the goal of both improving accuracy and reducing training time. The similar approach was used in the current experiment and publication.

Another valuable publication was made by leading of A. Esteva in 2017 called: «Dermatologist-level classification of skin cancer with deep neural networks» [2]. Representing automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions. Using deep convolutional neural networks (CNNs) as a great potential for general and highly variable tasks solver across many fine-grained object categories. Andres work demonstrates classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs. CNN was trained using a dataset of 129,450 clinical images – two orders of magnitude larger than previous datasets –consisting of 2,032 different diseases. Also the similar approach was used in the current work.

Purpose of this article is to determine the optimal method of image recognition for solving automation problems of constructing a 3D construction model.

Materials and methods. In this research, we use double neural network usage approach to determine and classify objects from image. Double neural network approach emerged from the synthesis of the algorithms represented in the reviewed related publications done before.

Results. The main reasons for replacing human participation in recognition tasks are to free a person from repetitive operations to solve other more important tasks and to improve the quality and speed of decisions making. This is the reason for the urgency of the tasks being solved.

A promising alternative to traditional methods of solving pattern recognition problems is neural networks (NN). This is an actively developing area of present day. The fields of application of neural networks are growing, new NA models are emerging, existing models are being adapted to solve new problems, etc. [3].

Artificial neural networks are mathematical models built on the principle of organization and functioning of biological neural networks – networks of nerve cells of a living organism [4].

Main features of neural networks are following listed below:

➢ Solving problems with unknown laws. Using the ability to learn on a variety of examples, the neural network is able to solve problems in which the laws of the development of the situation and the relationship between the input and output data are unknown. Traditional mathematical methods and expert systems in such cases are not applicable.

➢ Resistance to noise input. Ability to work in the presence of a large number of non-informative, noise input signals. There is no need to do their preliminary screenings, the neural network itself will determine their lack of suitability for solving the problem and discard them.

➢ Adaptation to environmental changes. Neural networks have the ability to adapt to environmental changes. In particular, neural networks trained to operate in a specific environment can be easily retrained to work in conditions of minor fluctuations of environmental parameters. Moreover, to work in a non-stationary environment (where the statistics change over time), neural networks can be created that are retrained in real time. The higher the adaptive capabilities of the system, the more stable its operation in a non-stationary environment.

➢ Potentially super high speed. Neural networks have the potential of ultra-high speed due to the use of mass parallelism of information processing.

➢ Fault tolerance in the hardware implementation of the neural network. Neural networks are potentially fault tolerant. This means that under adverse conditions, their performance drops slightly. For example, if a neuron or its connections are damaged, retrieving stored information is difficult. However, taking into account the distributed nature of information storage in the neural network, it can be argued that only serious damage to the structure of the neural network will significantly affect its performance. Therefore, the decline in the quality of the neural network is slow.

Artificial neural networks provide powerful flexible and versatile learning mechanisms, which is their main advantage over the other methods mentioned above. Training eliminates the need to choose key features, their significance and the relationship between features. But, nevertheless, the choice of the original input data significantly affects the quality of the solution. Neural networks have a good generalizing ability, that is, they can successfully spread the experience gained in the final training set to a variety of images.

Neural networks can be trained in a complex structure of images with less memory than is required for classification by structural methods. Training eliminates the need to choose key features and relationships between features. The parallelism of the work of neurons provides fast and high-quality pattern recognition.

Due to a good generalizing ability, artificial neural networks can successfully recognize images that are not shown in training, and also be resistant to noise in the input data.

The analysis of recognition methods and the numerous cases of successful use of artificial neural networks indicated in the literature, as well as the prospects of their development, led to the choice of the neural network method for constructing 3D structures.

Neural network is a complex of distributed and parallel computing systems capable of adaptive learning by analyzing the positive and negative effects and simulating simple biological processes occurring in the human brain. The transformative element in such networks is an artificial neuron (*figure 1*).

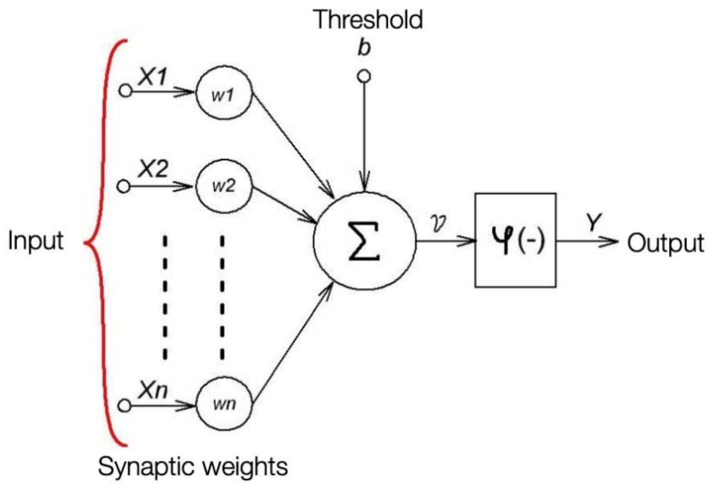

Figure 1. Artificial neuron model

Source: *compiled and systematized by the authors.*

The functioning of the neuron is described by the following expressions:

$$v = \sum_{j=1}^{n} \omega_j x_j \quad (1)$$

$$y = \varphi(v + b) \quad (2)$$

where x_j – input signals; ω_j – synaptic weights; φ (v+b) is an activation function that limits the amplitude of the output signal of the neuron; b is the threshold element; v is a linear combination of input actions; y is the output of the neuron; n is the number of inputs.

In *figure 2* shows the activation functions that have been spread in artificial neural networks.

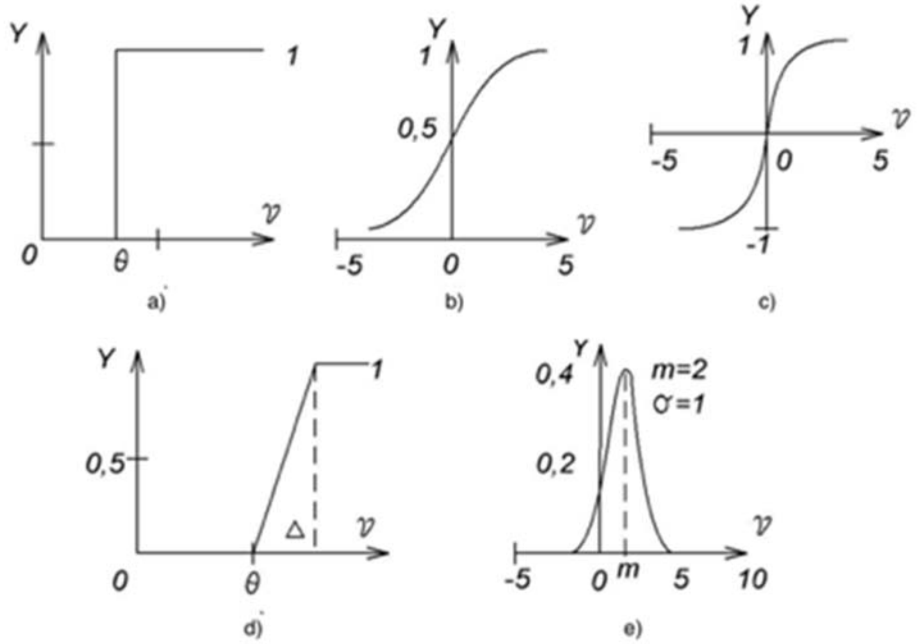

Figure 2. Types of activation functions: a) rigid step; b) sigmoid; c) hyperbolic tangent; d) flat step; e) Gaussian curve

Source: *compiled and systematized by the authors.*

In the general case, there are two main classes of neural network architectures – these are direct distribution networks and recurrent networks (networks with feedback).

In forward propagation networks, signals are transmitted strictly in one direction from the input (sensor) layer to the output one. If between the input and output layers in the network there is one or several hidden (associative) layers, then such a network is called multilayered. Forward propagation networks include single-layer and multilayer perceptron, networks of radial basis functions.

Recurrent neural networks are distinguished by the presence of at least one feedback. In networks with feedback, information from subsequent layers is transmitted to previous layers. The presence of feedback has a direct impact on the ability of recurrent networks to learn and their performance. Examples of such networks are competitive networks, the Kohonen network, the Hopfield network, models of the theory of adaptive resonance [4].

Training of a neural network consists in changing the internal parameters of the network so that the output of the artificial neural network generates a vector of values that coincides with the results of examples of the training sample. There are various learning algorithms that differ from each other in the way of tuning the synaptic weights of neurons [4; 5].

The formulation of the recognition problem assumes that the initial information about the classes is given by a sample of vector attribute descriptions of domain structure objects representing all nine classes. As such features, five geometric features were used – the form coefficients (*table*) and the Euler number (topological feature).

Table

Form factors

Coefficient name	Formula
Roundness coefficient	$k_{round}=\frac{4\pi S}{P^2}$
	S is the area of the object; P is the perimeter of the object
Fill factor	$k_{fill} = \frac{S}{hl}$
	h and l are the dimensions described around rectangle object
Eccentricity of the ellipse	$e = \sqrt{1 - \left(\frac{b}{a}\right)^2}$
	b and a big and small semi ellipse
Compactness factor	$k_{comp} = \frac{S}{S_1}$
	S_1 is the area of the convex polygon into which the object is inscribed
Perimeter Ratio	$k_{per} = \frac{P_{obj}}{P_{rect}}$
	P_{obj}– the perimeter of the object; P_{rect} – the perimeter of the rectangle described around the object.

Source: compiled and systematized by the authors.

For test purposes an image of the floor plan with nine types of classified objects was formed. The total number of objects was 11,000. As input, a characteristic vector containing six initial features describing the shape of the objects was used.

In *figure 3* shows the location of objects in the space of informative features, presentedin *table*.

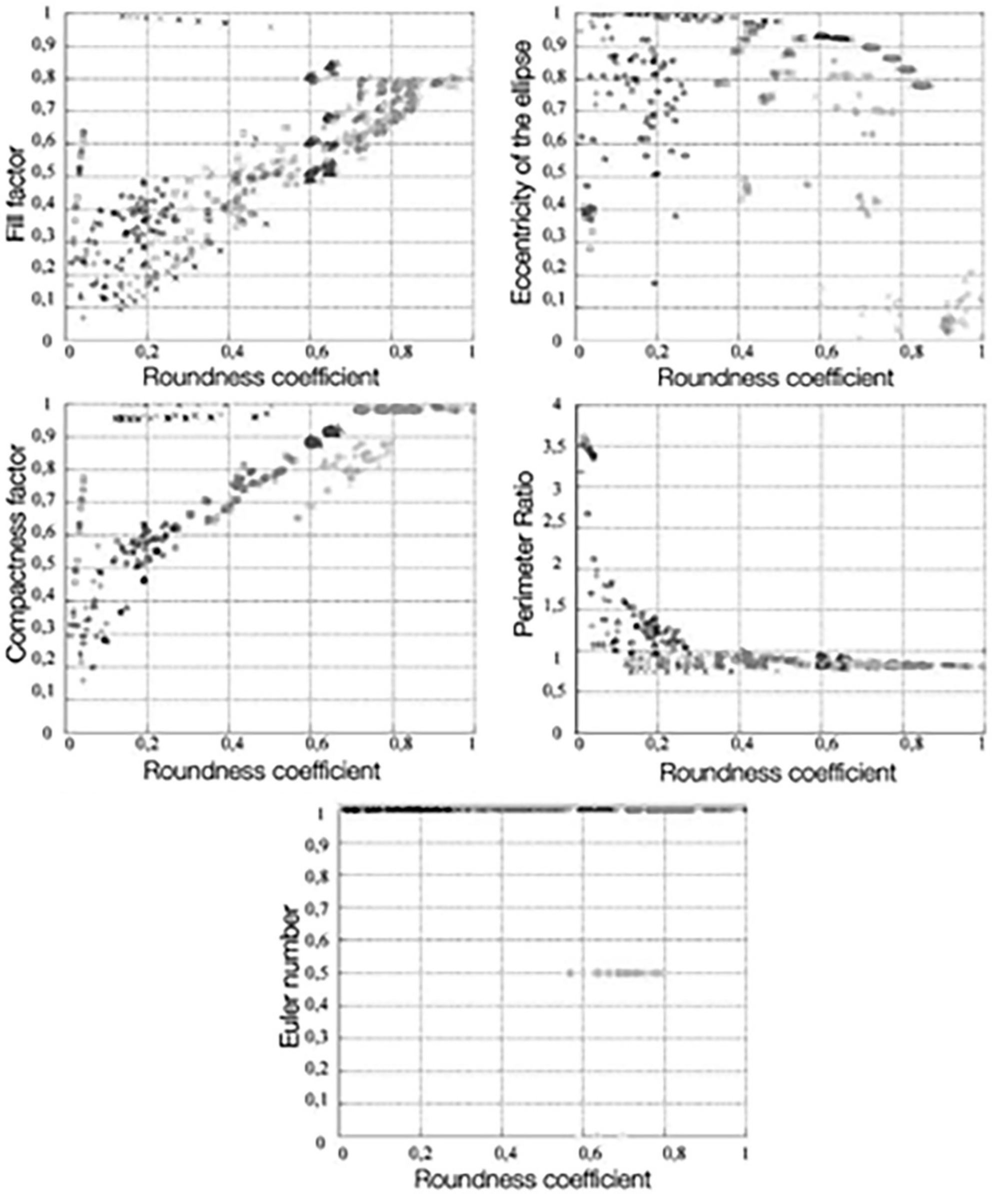

Figure 3. The division of objects into classes in the system of informative features

Source: *compiled and systematized by the authors.*

From the obtained results it is clear that the classes overlap each other, so they are poorly separable. It is proposed to perform the classification of these objects in several stages, as shown in *figure 4* structure with the use of two neural networks of direct distribution.

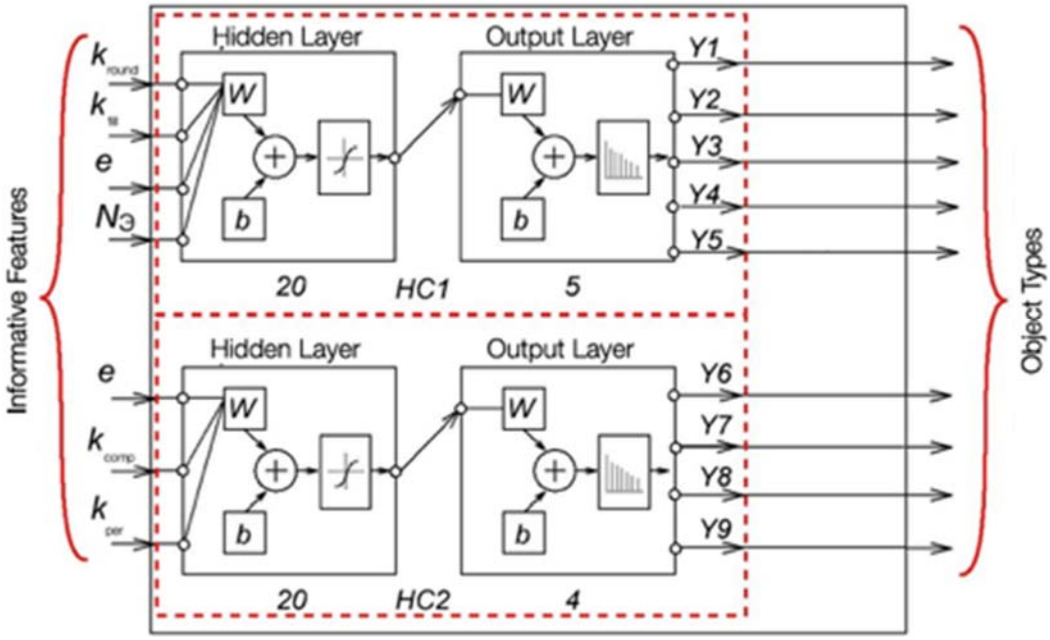

Figure 4. The structure of the algorithm for object recognition

Source: compiled and systematized by the authors.

The object to be classified is given by the vector of informative features K = ($k$round, $k$fill, e, $k$comp, $k$per, Ne). The first neural network uses four informative features $K1$ = ($k$round, $k$fill, e, NE) and assigns the object to one of the classes $\{y1, y2, y3, y4, y5\}$.

For the neural network, controlled learning was performed, i.e. training with a "teacher" [4]. The method of scaled bound gradients with the error function — cross-entropy [6] was used. For network training, an image was formed with 1403 ideal objects located at different angles and having different sizes. Network training was conducted on the basis of a constructive approach, according to which training begins on a small neural network, which gradually increases until the required accuracy is achieved according to the test results. The minimum recognition error was obtained with 20 neurons in the hidden layer.

The second neural network uses three informative features $K2$ = ($k$com, $k$per) and classifies objects into four classes $\{y6, y7, y8, y9\}$.

For learning the second neural network, an image with 574 ideal objects was formed. The same training methods were used as the first neural network.

As an activation function for the neurons of the hidden layer of the first and second networks, the tangent function was used, and for the neurons of the output layer, a competing function with a soft maximum.

The example of a neural network allows you to define and classify each element. Each class is highlighted in its own color. Further application of the obtained data can be applied to build 3D models from predefined parameters for each class [7].

Method for recognizing images of objects and structure is proposed. The recognition algorithm is based on two two-layer neural networks of direct distribution, which allow to recognize and classify objects having different shapes. As informative features of objects on the basis of which neural networks carried out the classification. The proposed method can be used to recognize images of objects that are similar in shape.

This article represents results of compiled classification of types on the basis of practical results and a literature review. The features of classification that significantly affect the choice of methods and algorithms for solving problems are considered.

This method allows classification and definition of simple and complex shapes and can be used for analyzing images. This approach of classification is fully implemented in the software approach.

Conclusion. Proposed neural network allows to define and classify each element. Each class is highlighted in its own color. Further application of the obtained data can be applied to build 3D models from predefined parameters for each class.

Proposed method for recognizing images of objects and structures seems to be most profitable. The recognition algorithm is based on two two-layer neural networks of direct distribution, which allow to recognize and classify objects having different shapes. As informative features of objects on the basis of which neural networks carried out the classification. The proposed method can be used to recognize images of objects that are similar in shape.

REFERENCES

1. Alexandre, L.A. (2016). 3D Object Recognition Using Convolutional Neural Networks with Transfer Learning Between Input Channels. In: Menegatti E., Michael N., Berns K., Yamaguchi H. (Eds). Intelligent Autonomous Systems 13. Advances in Intelligent Systems and Computing. (vol. 302). Springer, Cham [in English].
2. Andre, Esteva, & Brett, Kuprel (2017). Dermatologist-level classification of skin cancer with deep neural networks. (Vol. 542), (pp. 115–118).02 February. Retrieved from https://www.nature.com/articles/nature21056?TB_iframe=true&width=914.4&height=921.6 [in English].
3. Popescu, A. C., & Farid, H. (2005). Exposing digital forgeries by detecting traces of resampling. *IEEE Transactions on signal processing*. (Vol. 53), *2*, (pp. 758-767) [in English].
4. Qian, Y., Dong, J., Wang, W., & Tan, T. (2015). Deep learning for steg analysis via convolutional neural networks. *Media Watermarking, Security and Forensics*. (Vol. 9409), (pp. 94 090J) [in English].
5. Lin, M., Chen, Q., & Yan, S. (2014). Network in network, in International Conference on Learning Representations [in English].
6. Ciresan, D.C., Meier, U. J., Masci, Gambardella L.M., & Schmidhuber J. (2011). High-performance neural networks for visual object classification. Arxiv preprint arXiv:1102.0183 [in English].

7. Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks, in Advances in neural information processing systems, (pp. 1097-1105) [in English].

The article submitted to editor's office on 27.05.2019.

Криворучко О., Хорольська К., Чубаєвський В. Застосування нейронних мереж у розпізнаванні зображень.

Постановка проблеми. *Дослідницьке поле комп'ютерної візуалізації істотно змінилося протягом останніх років, здебільшого завдяки досягненням у сфері глибокого навчання. У цей час глибокі нейронні мережі успішно використовувалися в різних практиках. Зокрема, згорткові нейронні мережі змогли досягти найсучасніших результатів у задачі з розпізнавання зображень, у багатьох випадках перевершуючи людські можливості. Попри значну кількість досліджень, проведених у цій сфері, більшість праць розглядають набір даних, що складаються з досить високоякісних зображень. У реальних додатках, однак, ми часто стикаємося з проблемами, де потрібно робити багато ручної роботи. У цій статті основна увага приділяється функціонуванню класифікації патернів зображень. Класифікаційна характеристика є важливою частиною, що вирішує ряд актуальних задач: від створення єдиної інформаційної мови для автоматизованих систем до уніфікації та стандартизації.*

Метою *роботи є визначення оптимального методу розпізнавання зображень для вирішення проблеми автоматизованої побудови конструкційних 3D моделей.*

Матеріали та методи. *Застосовано подвійний підхід до використання нейронних мереж для визначення та класифікації об'єктів із зображення. Подвійний нейромережевий підхід виник з синтезу алгоритмів, представлених у розглянутих раніше публікаціях.*

Результати дослідження. *Для тестових цілей сформовано план основи зображення з дев'ятьма типами класифікованих об'єктів. Загальна кількість об'єктів становила 11 тис. Вхідними даними слугував характерний вектор, який містить шість початкових ознак, що описують форму об'єктів.*

Запропонований підхід з подвійною нейронною мережею використано для розпізнавання та класифікації об'єктів на зображенні. Після процесу контрольованого навчання нейронних мереж, тобто навчання з «вчителем», вони були повністю в змозі визначити об'єкти на зображенні.

Висновки. *Запропонована нейромережа дає змогу визначати і класифікувати кожен елемент. Кожен клас підсвічується певним кольором. Подальше застосування отриманих даних може бути застосовано для побудови 3D моделей з попередньо визначених параметрів для кожного класу.*

Запропонований спосіб розпізнавання зображень об'єктів і структур вбачається найбільш вигідним. Алгоритм розпізнавання базується на двох двошарових нейронних мережах прямого розподілу, які дають змогу розпізнавати і класифікувати об'єкти різної форми. Як інформативні ознаки об'єктів, на основі яких нейронні мережі здійснюють класифікацію, запропонований спосіб може бути використаний для розпізнавання зображень об'єктів, схожих за формою.

Ключові слова: нейронна мережа, об'єкт розпізнавання, класифікація, домени.