

# APPLICATION OF A CONVOLUTIONAL NEURAL NETWORK WITH A MODULE OF ELEMENTARY GRAPHIC PRIMITIVE CLASSIFIERS IN THE PROBLEMS OF RECOGNITION OF DRAWING DOCUMENTATION AND TRANSFORMATION OF 2D TO 3D MODELS

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## ABSTRACT

This paper presents the results of the research related to the design of a convolutional neural network with a module of graphic primitives elementary classifiers (EC) in the tasks of drawing documentation recognition and transformation of the 2D into 3D models. An architecture of a convolutional neural network with an elementary classifiers module of graphic primitives was proposed for solving the drawing recognition and 2D → 3D transformation problem. A graphic image classifier model based on covered classes and elementary primitive classifiers has been developed to increase the effectiveness of CNN training.

**Keywords:** *Information Protection, Information Security, Organizational and Economic Support, Infrastructure Management, Decision Support System, Risk Minimization.*

## 1. INTRODUCTION

With the development of information technologies (IT) and its integration into production (regardless of the target direction - mechanical engineering, light industry, furniture manufacturing, medicine, etc.), it is possible to reasonably speak of a global trend to abandon traditional paper carriers of design documentation, for example, drawings and blueprints. The transition to electronic media not only facilitates more convenient procedures related to editing, replication, storage, transmission, etc. of digitized data, but also forces faster transition to the new technologies. Such a tendency fully applies to the task of moving from 2D product modeling to 3D models.

Two-dimensional drawings (hereinafter referred to as 2D) are often difficult to understand. It is not always convenient for designers to make adjustments to such 2D models. Accordingly, the creation of IT-based systems for automatic reconstruction (recognition) or conversion of 2D models into 3D (models or 2D → 3D) will allow to

repeatedly reduce not only the complexity and time for new products design process or the modernization process of existing ones, but also allows one to visualize the appearance of the product for a potential customer or buyer who does not have deep knowledge in the field of spatial interpretation of 2D models.

As noted by a number of researchers [1, 2], and taking into account the fact that enterprises and organizations have accumulated huge blueprint and design documentation sets, the development and improvement of methods, models, and IT, contributing to the automation of recognition and the subsequent conversion of 2D into 3D (hereinafter 2D → 3D), models is an actual scientific and technical problem. It should also not be forgotten that the digitization procedure of existing traditional paper documentation is not only a time-consuming process that takes hundreds, and sometimes even thousands of man-hours, but it is also associated with the need to solve parallel tasks. Such tasks include, for example, the need to protect the obtained 3D models, for example in case the model of a specific

product is related to the military sector, or simply being the intellectual property of its owner.

It should be noted that without modern technologies and systems of artificial intelligence (AI) it is difficult to solve such a problem, which itself creates a new research problem. Namely, the development of mathematical models for AI in the tasks of 2D images recognition for their subsequent conversion into a 3D model.

Therefore it was assumed that the use of the neural network is suitable for the task of the  $2D \rightarrow 3D$  transformation. At this point the architecture of the convolutional neural network (CNN) and most important image classifier that increases the possible performance rate of the convolutional neural network should be proposed.

## 2. LITERATURE REVIEW AND ANALYSIS

During the 2022 there was no fundamental research on the current topic. Most of the topics during 2022 are devoted to analysis of the hyperspectral image classification [43-45, 50-51]. In [46] authors propose a combined algorithm of the CNN along with the regularized extreme learning machine. Which is a solid approach and mainly proves the advantage of the combined algorithms compared to the single-algorithm approach. Another work [47] provides mainly the analysis of the optimization problem and incomplete data issue of image classification using the CNN with only a small amount of knowledge annotation, solving the overfitting problem of the CNN. In the article [48] authors provide more general analysis of the CNN application in image processing. As well as [47] authors of the [48] are dealing with the overfitting phenomenon. Their research is based on the usage of the VGG16 model. The authors proposed the so-called Batch Normalization method. Nevertheless the algorithm has advantage on the relatively small dataset and was tested during 300 iterations, which is not enough to make a solid decision on the real algorithm performance in terms of error rate.

Sticking to the main topic of this research it should be noted that many researchers emphasize that traditional 2D systems are still widespread among many enterprises and continue to be used at different stages of production [1, 2]. Although 3D modeling of objects is gaining more and more supporters among designers and manufacturers, and it is also mathematically described in detail in works [3-10], 2D systems remain in demand due to the following factors [11-23,41-42, 49]:

1) wide possibilities of input both in manual mode (classic drawing documentation on paper media) and with the use of the two-dimensional

geometric, graphic, explanatory, alphanumeric and other applications.

2) a wide range of possibilities for editing existing documentation up to those that were created several decades ago. Not resorting to the use of IT for recognition and/or digitization of existing documentation;

3) presence of huge paper-based drawing documentation sets at the enterprises, especially in the field of mechanical engineering. Moreover, paradoxically, in some cases this is a more secure storage option than drawing documentation digitized and stored on electronic media, access to which can be obtained by unauthorized intruders, competitors or enemy states;

4) it is enough for the developer to use a relatively simple analytical device to make changes to the project during the editing process of the information presented on the 2D models or in the 2D systems. For example, the majority of such changes require only knowledge of the basics of a geometric two-dimensional coordinate system built on planes. And if such documentation is done with sufficient quality, then the subsequent  $2D \rightarrow 3D$  transformation procedure will not present any difficulties;

5) 2D systems provide users with many opportunities and tools for extraction of the information that characterizes the geometry of both the object as a whole (for example, overall dimensions) and its projections (for example, its area). Subsequently, such information may be required when planning production and placing technological equipment in the corresponding area;

6) modern 2D systems with automatic or automated  $2D \rightarrow 3D$  transformation procedures usually contain a minimum set of data for 3D models to be obtained by themselves. Such data can include, for example, the coordinates of the points corresponding to the vertices of the projections of the 3D modeling object sides. Such data exists in CAD, for example, Autodesk TinkerCAD, DesignSpark Mechanical, FreeCAD, Autodesk AutoCAD, ZBrush, Blender, etc.

However, despite the factors listed above, 3D models are gradually winning their positions, possessing a large number of advantages that were discussed at the beginning of this scientific paper.

## 3. MODELS AND METHODS

As it was shown in scientific works [23-27], the use of classical ANNs in the task of graphic information recognition, including drawing documentation, will not give the proper effect due to the following reasons:

- recognizable images on the drawing documentation, as a rule, are characterized by a large size. Therefore, the size of the NN is growing;
- the first reason automatically makes it necessary to have a sufficiently large training sample. Such a sample is difficult to implement in practice, taking into account the huge variety of nomenclature of drawing documentation. In addition, operations with such large data sets lead to an increase in training time. And the training procedure itself becomes more complicated as the image of the details projections on the drawings becomes more complicated;
- although the use of two or more ANNs at different stages of the drawing documentation recognition problem solving process has a positive effect, but it does not radically reduce the total solution time, and also does not lead to a significant reduction in overall solution time;
- classical ANNs, as shown by a number of applied studies [24-26], do not give acceptable results in the case of image invariance, as well as during the change in scale of the image.

Based on the above, convolutional neural networks (hereinafter referred to as CNN) were chosen to solve the problem of drawing recognition and  $2D \rightarrow 3D$  transformation.

Each convolutional neural network layer [28-31] can be conventionally represented as a set of planes, see Fig. 1. In turn, each plane will consist of neurons. The neurons of the corresponding plane are characterized by the same synaptic coefficients. Each of the neurons in the corresponding layer will receive the input image of the previous layer.

Convolutional neural network is a multilayer perceptron [28].

Let one consider the stage of feature extraction. Each neuron receives input signals from a local receptive field located in the previous layer. At this stage, the procedure for limited features extraction is implemented. Once a feature has been extracted, its subsequent location will not matter.

Next step is to consider the feature mapping stage. As shown in Figure 1, the computational layers of the CNN network include sets of so-called feature maps [28-31].

Each feature map can be represented as a plane. On this plane, neurons share their set of synaptic weights [29].

Further, let one consider the subsampling stage. Behind the respective convolution layers in Figure 1 there are the computational layers. Each such computational layer provides the operation of local averaging and subsampling [29, 30].

Local averaging makes it possible to reduce the resolution for feature maps [29, 30]. In fact, it provides a weakening of the sensitivity of the output signals of the feature mapping operators [29, 30].

Figure 1 represents the CNN scheme, which includes one input, four hidden and one output layer of neurons with its structure. Such a network is suitable for handwriting recognition [29-31]. Although such a task is important for drawing documentation recognition, it is not focused on the drawing primitives recognition. Therefore, it can rather be an integral part in solving the general task of the study.

ANN learning process is needed to recognize images that make up an image in a drawing or drawing primitives (lines and arrows; rectangles; circles, ellipses, arcs, segments and sectors; curves; connecting lines; three-dimensional objects (cubes, balls, cylinders, tori, etc.) ; text data), for example, as shown in Fig. 2

To ensure the unambiguity, completeness and integrity of the existing primitives classification sets involved in the processes of drawing and technical documentation recognition and subsequent transformation  $2D \rightarrow 3D$ , the following requirements for the classification of primitives involved in the above mentioned processes should be introduced:

- non-intersecting classes of graphic primitives (determines the unambiguity of class selection based on an external rule that allows making a decision);
- applicability (adding a class should not cause more than one class to be split into two parts);
- objectivity (the presence or absence of a class must be confirmed by known classifications);
- extensibility (adding a class is possible by splitting existing classes);
- the number of classes is finite.

Various data can become the basis for constructing elementary classifiers (EC) of primitives for CNN used in the processes of recognition of drawing and graphic documentation.

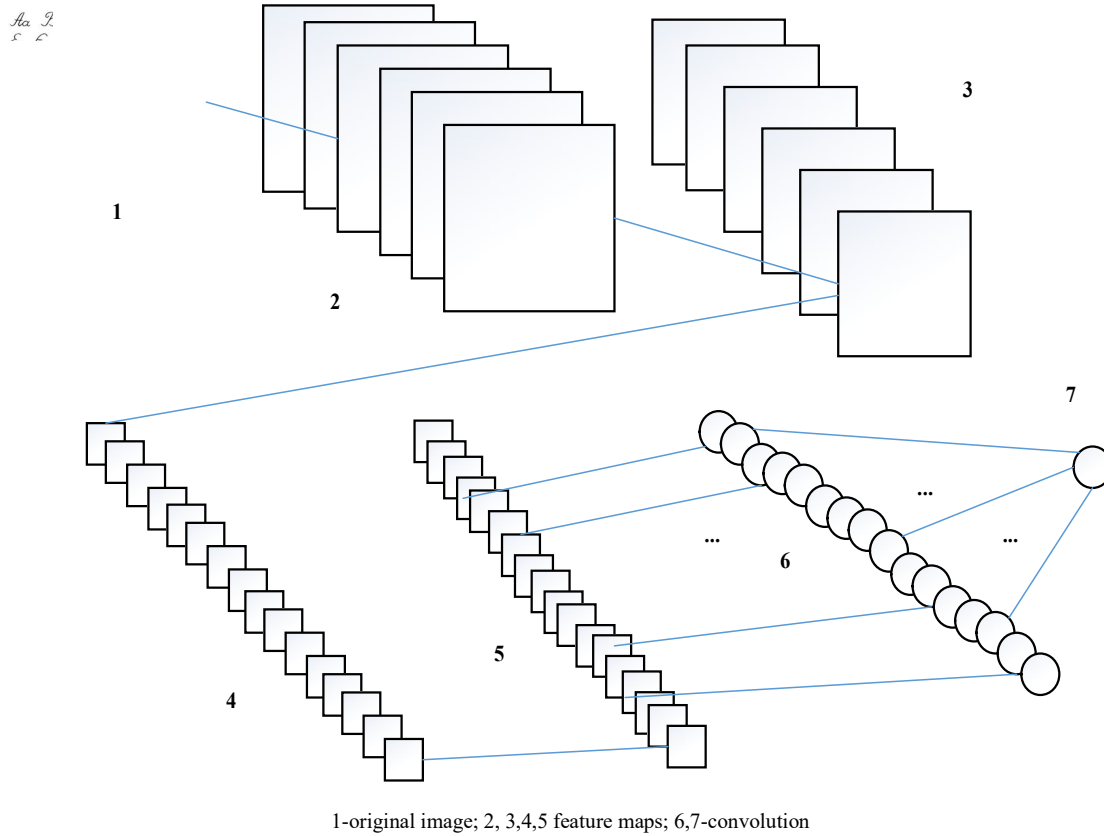


Figure 1. CNN scheme for handwriting recognition, (includes one input, four hidden and one output layer of neurons) [29-31]

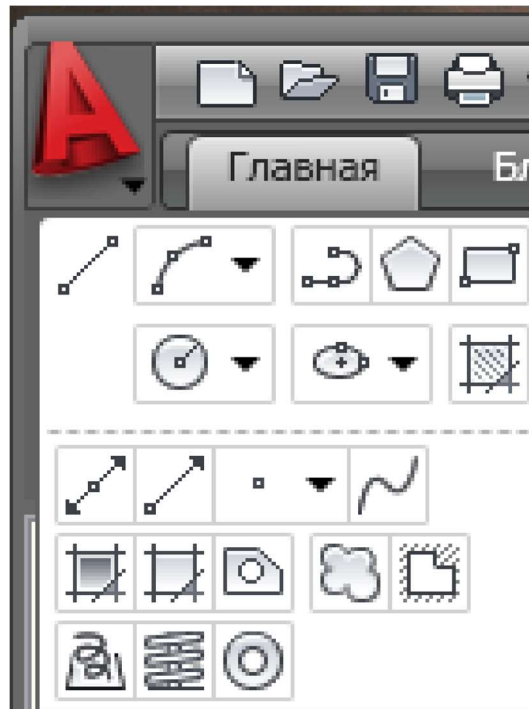


Figure 2. An example of primitives for an image formation in AutoCAD

For example, descriptive information that is presented in the form of a binary representation of the points coordinates in the original drawing

$$\{P_{ax1}, \dots, P_{axn}\}$$

Let one consider following:

$MI$  - the total number of primitives used for the training procedure and subsequent recognition;

$PA$  - the number of potential primitives for a specific area of drawing and technical documentation (engineering, construction, etc.);

$B_{Pa}$  - set of actual primitives numbers, during CNN training procedures.

In general, the problem of drawing and technical documentation recognition is as follows [27-31].

Let one examine a set of objects, in the case of this study it is  $PA$  - the number of potential primitives (including alphanumeric ones). Objects that can be attributed to this set are characterized by a set of features  $\{P_{ax1}, \dots, P_{axn}\}$ . It is known that the set  $PA$  is represented as a union of subsets (classes) of primitives -  $(KL_1, \dots, KL_l)$  or  $(B_{Pa1}, \dots, B_{Pal})$  which are not intersecting.

Suppose there is a finite group of objects  $\{SP_{a1}, \dots, SP_{am}\}$  from  $PA$ , about which it is known, to which classes of primitives they can be attributed. These are precedents, i.e. objects used for training (hereinafter OUT) CNN. It is necessary for CNN to classify these objects according to the existing set of parameters (features), i.e. using the description of the object  $SP_{an}$  from the  $PA$ . Then, based on the results of the classification, the work of an automated or automatic system for drawing and technical documentation recognition is built. The CNN does not initially know what class the object in the drawing belongs to. It can be a machine part, a pipe, a building structure, etc.

Automation of the search for new primitives involves the use of models based on a feature description combinatorial analysis  $\{SP_{a1}, \dots, SP_{am}\}$ . In the works [32-35], it was shown that these methods give an acceptable recognition result in a situation where the data was presented in a discrete form and the number of allowed feature values was small [22].

An exceptional feature of the proposed EC implementation procedures for graphic primitives on drawing and technical documentation recognition is the ability to obtain CNNs training results even in a situation where there is no data on functions that describe the distribution of feature values of these

primitives. Such procedures will henceforth be called logical procedures.

The task is to minimize the training sample for image recognition within the class, for example, only for the sphere of engineering drawings. At the same time, there is no need to set the so-called metrics in the space of object descriptions that characterize each class of graphic primitives.

The paradigm of building a base of primitives for CNN learning process (or logical procedures for learning LPO) is to find informative fragments descriptions of the corresponding graphical primitives. These fragments, when creating specific design solutions for drawing and construction documentation recognition systems, for example, based on CNN neural networks, will make it possible to unambiguously draw a conclusion about the presence (or absence) in the base of the recognition system of a certain graphic primitive within the class.

Let one put the fragments that reflect the characteristic patterns in the description of the object used in the course of CNN training in the tasks of drawing and technical documentation recognition as informative. Then, the presence (absence) of a fragment(s) in the description of an object that is undergoing classification makes it possible to attribute it to a certain class. In the LPO, one sets as informative a fragment(s) that is present in the object descriptions of the considered graphic primitives class, but is absent in the object description of other classes. The considered fragments must be supplemented with descriptions in terms of CNN design.

During the construction of an LPO for convolutional neural network, elementary classifiers (EC) proposed by a number of authors [36-40] were used. EC is a fragment that describes an object. In turn, this object is used to train convolutional neural network in the tasks of drawing and technical documentation recognition. For each class of images  $(KL_1, \dots, KL_l)$ , a set of ECs is constructed with predetermined parameters.

At the same time, the subsequent reasoning for the EC is based on such a hypothesis, consisting of two assumptions:

1) ECs that being used are those present in the objects descriptions of the currently analyzed class (for example, engineering drawings), but they are not in the objects description of other classes;

2) a descriptive set of indicators (features) for the corresponding graphic primitive was given in binary form (for example, 00101010). At the same time, OUT characterizes all objects of this class. And, therefore, OUT has a greater information content.



In order to improve the efficiency of LPO, the relevant problem of the property of "non-occurrence" of groups from acceptable values of indicators of graphic primitives usage.

In addition, it is necessary to implement a "decision rule"  $DR(p_{axi})$  in the recognition algorithm for CNN with a minimum number of errors in its work.

The next problem of a CNN design is the presence of an OUT with characteristics that lie at the junction of different classes of graphic primitives in the sample, for example, a square-rectangle or a circle-oval. Such OUT is atypical for its class. It is due to the similarity of informative signatures, since indicators presented in binary form are generally close. The presence of atypical OUTs in the training set (TS) increases the length of informative subscripts of graphic primitives. Thus, it will be possible to distinguish between objects from different classes. And since long informative labels are not often found for new objects, it leads to an increase in the number of unrecognized elements of graphic and drawing documentation.

The synthesis of algorithms for efficient LPO implementations for CNN is related to the result of the quantitative assessment analysis of the fragments sets informativeness, i.e. indicators of graphic primitives.

When solving tasks related to the design of efficient CNNs, correct data on the structure of the entire recognition object in some situations may not be available. Therefore, initially, during the synthesis of LPO, the correctness of their use on new objects that are different from  $\{sp_{a1}, \dots, sp_{am}\}$  is not guaranteed.

In other words, those primitives that have been trained for engineering drawings will not work for the construction industry, although visual similarity may be present. At the same time, if OUTs have the characteristics inherent in the analyzed set  $\{sp_{a1}, \dots, sp_{am}\}$ , then the algorithm that works flawlessly at the stage of convolutional neural network learning will provide acceptable results on

unclassified  $sp_{an}$  that were not included in the OUT sample. In this regard, in the works of authors [37-39], the problems of the correctness of the algorithms for recognition using CNNs were paid attention. The algorithm is correct if it correctly recognizes objects from the test set.

The efficiency of the algorithm can be checked using the simplest procedure. The analyzed object  $sp_{an}$ , for example, descriptive indicators (DI) of a

graphic primitive, etc., was compared with each of the OUTs  $\{sp_{a1}, \dots, sp_{am}\}$ .

If the DI of the object  $sp_{an}$  is identical to the DI of the OUT  $sp_{ai}$ , it should be attributed to the class to which  $sp_{ai}$  belongs. Otherwise, the algorithm will issue a message about the rejection of recognition. The algorithm is operable [66], but it is

not adapted to recognize any  $sp_{ai}$  object whose DI is not identical with the DI of the OUT available in the repository [37-40].

A more convenient way to solve one of the local problems of drawing and technical documentation recognition using CNN was proposed. In this case, it is possible to perform a transition from the original space of object descriptions  $P_{axj}$ , in the form of a binary representation of features, to a new space  $NEP_{ax}$  using transformation  $P_{axj} \rightarrow NEP_{ax}$ .

Let one assume that  $NP_{pa}$  is some selection of  $r_{pa}, r_{pa} \leq MI$  discrete indicators (for example, the coordinates of the points of the original image, the type of lines (solid, dotted, dashed, etc.) in the form  $\{p_{aj1}, \dots, p_{ajr}\}$ . The distance between objects  $sp'_a = (cp'_{a1}, cp'_{a2}, \dots, cp'_{aMI})$  and  $sp''_a = (cp''_{a1}, cp''_{a2}, \dots, cp''_{aMI})$  from the PA according to the set  $NP_{pa}$  was estimated by the value:

$$BN(sp'_a, sp''_a, NP_{pa}) = \begin{cases} 1, & \text{if } cp'_{jti} = cp''_{jti} \text{ at } ti = 1, 2, \dots, r_{pa}, \\ 0 & \text{in other case} \end{cases} \quad (1)$$

In the system of OUT indicators  $\{p_{a1}, \dots, p_{aMI}\}$ , one can single out a set of subsets of the form:  $NP_{pa} = \{p_{aj1}, \dots, p_{aMI}\}$ ,  $r_{pa} \leq MI$ .

The distinguished subsets will be assumed to be the support sets (SS) of the ARC. Let's denote their entire set -  $\Omega MI$ .

Set the following additional parameters:

$po_{sp_a}$  - parameter characterizing the significance of the object  $SP_{ai}$ ,  $i=1, 2, \dots, PA$ ;

$po_{NP_{pa}}$  - a parameter characterizing the significance of the OM object  $NP_{pa} \in \Omega MI$ .

Let one calculate the score by comparing the  $SP_{an}$  object with each OUT for the CNN  $SP_{ai}$  for each  $OM$ .

For each class of graphical primitives used to train the CNN  $KL$ ,  $KL \in \{KL_1, \dots, KL_l\}$ , one can calculate the estimate whether  $\Gamma(sp_a, KL)$  of the object  $SP_a$  belongs to the  $KL$  class:

$$\Gamma(sp_a, KL) = \frac{1}{|LW_{KL}|} \sum_{sp_{ai} \in KLINP_{pa}} \sum_{p_{ai} \in \Omega MI} p_{ai} \cdot po_{NP_{pa}} \cdot BN(sp_a, sp_{ai}, NP_{pa}), \quad (2)$$

where

$$|LW_{KL}| = |KL \cap \{sp_{a1}, \dots, sp_{aMI}\}|.$$

The object  $SP_{an}$  belongs to the class with the highest score. If there are many such classes, then the algorithm refuses further recognition. To improve the correctness of the algorithm, it is necessary to solve the following system of inequalities:

$$\begin{aligned} \Gamma(sp_{a1}, KL_1) &> \Gamma(sp_{a1}, KL_2), \\ \Gamma(sp_{aMI_1}, KL_1) &> \Gamma(sp_{aMI_1}, KL_2), \\ &\dots \\ \Gamma(sp_{aMI}, KL_2) &> \Gamma(sp_{aMI}, KL_1). \end{aligned} \quad (3)$$

To solve system (3), it is necessary to choose the parameters  $po_{sp_{ai}}$   $i = 1, 2, \dots, PA$ , and  $po_{NP_{pa}}$ ,  $NP_{pa} \in \Omega MI$ .

When a system is incompatible, it is necessary to find the maximum compatible subsystem for it. Then, from the solution of this subsystem, determine

the values  $po_{sp_{ai}}$  and  $po_{NP_{pa}}$ .

For example, select a set in such a way that the condition  $\Gamma(sp'_a, KL) = 0$  was fulfilled for any  $sp'_a \notin KL$  OUT. In addition, for any  $sp''_a \in KL$

OUT, the inequality  $\Gamma(sp''_a, KL) > 0$  was satisfied.

It can be implemented in the following way.

Let  $NP_{pa} = \{p_{aj_1}, \dots, p_{aj_{MI}}\}$  is OM.

The set of  $NP_{pa}$  indicators (or features) will be considered as satisfying the requirements of the test

if for each  $sp'_a, sp''_a$  OUT, and at the same time, belonging to dissimilar classes, the condition can be applied.

$$BN(sp'_a, sp''_a, NP_{pa}) = 0 \quad (4)$$

Thus, a test is a group (selection) of indicators, according to which only any two objects from different classes differ.

Considering the previous calculations, it can be argued that some images will be fed to the CNN input (digitized data in binary form - encoded images). In turn, at the output of the CNN, we have the required type of image based on the network's interpretation of a simple correspondence of a set of object class/classes.

Therefore, one can conclude. The input signal can be treated as a constant conditional value. The output signal will be a discrete value. With such a combination for the EC apparatus usage and the CNN itself, an advantage can be obtained over the usual procedure of recognition with use of neural networks. Namely, the network adaptability property arises, which, after training, will be able to work with different recognition objects classes, as shown in Figure 3.

Due to the adaptability property, such a CNN, will be able to quite effectively recognize different graphic images belonging to different types of graphic primitives.

Following features are present in the proposed architecture of a convolutional neural network for solving the problem of drawing recognition and  $2D \rightarrow 3D$  transformation, see fig. 3:

- a module for synthesizing a hypothesis that an object belongs to a certain class of graphic primitives. This module is intended for the synthesis of hypotheses that are responsible for the coordinates determination of a particular object in the image, which is important for the subsequent sets of indicators (attributes) obtain for the corresponding graphic primitive;
- a module with elementary classifiers, which actually forms a convolutional neural network.

As for the architecture and direct experience of using convolutional neural network for solving image recognition problems, a rather large number of previously mentioned works are devoted to this issue.

In these works, and also, taking into account the controversy of the conclusions made in [11-40], it can be stated that with the development of recognition technologies and the growth of computing power of computer technology, it became possible not only to increase the efficiency of

recognition systems based on convolutional neural network, but also train these networks more efficiently. Moreover, the effectiveness of such training directly depends on the successful solution of image classification problems.

The foregoing determines the relevance of solving the following problem - building a graphic image classifier model based on class coverage and elementary classifiers of primitives to improve the efficiency of CNN training.

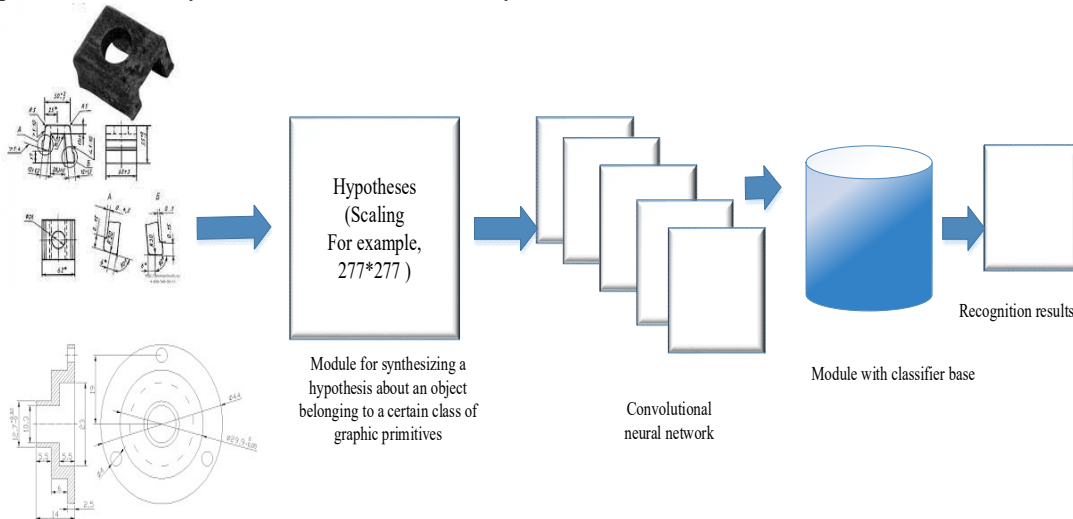


Figure 3. Schematic diagram of a CNN with a graphic primitive EC module for drawing and technical documentation recognition (developed by the author)

The basic rules for designing elementary classifiers for graphic primitives in drawing and technical documentation recognition are presented below.

EC data can form the basis of the EC module shown in Figure 3.

Let's match the EC of the object:

$$(\sigma_{DOP}, NP_{pa}) \quad (5)$$

where,  $\sigma_{DOP} = (\sigma_{DOP_1}, \dots, \sigma_{DOP_r})$

$NP_{pa}$  - a set of indicators of graphic primitives on the drawing and technical documentation with numbers  $j_1 \dots j_{r_{pa}}$  and elementary conjunction

$$\mathfrak{R} = p_{axj_1}^{\sigma_{DOP_1}} \dots p_{axj_{r_{pa}}}^{\sigma_{DOP_{r_{pa}}}}$$

If  $sp_a = (\alpha p_{a1}, \dots, \alpha p_{aMI})$  is an object from the set  $PA$ , then, obviously,  $BN(\sigma_{DOP}, sp_a, NP_{pa}) = 1$  if

and only if  $(\alpha p_{a1}, \dots, \alpha p_{aMI}) \in NI_{\mathfrak{R}}$ , where  $NI_{\mathfrak{R}}$  is the truth interval of the elementary conjunction  $\mathfrak{R}$ .

For graphical display of drawing primitives in such a popular drawing system as Autodesk AutoCAD, ActiveX technology was used. An alternative option is the ability to use the built-in AutoLISP programming language. The syntax of the latter is closer to the idea of using EC, since it allows you to work directly with arrays of points that define the coordinates of a two-dimensional projection.

The mutual arrangement of drawing primitives can be described based on adjacency matrices. So, for example, columns will describe arcs or circles, and rows will describe line segments. In this case, at the intersections of rows and columns there will be numbers that determine the adjacency of drawing primitives. In the elementary classifiers module, which was previously shown in Figure 3, one can save all the matrices that define the template of products of a certain category.



When designing a convolutional neural network with a module of elementary classifiers of graphic primitives for recognition of drawings and technical documentation, it should be taken into account that the definition of a set of ECs is reduced to finding permissible and maximum conjunctions for the characteristic function of an  $(KL_l) = (B_{p_{al}})$  object class. The classes of  $B_{F_{KL}}$  primitives on the drawing and technical documentation include the simplest images shown in Figure 2.

Moreover, this function is a two-valued logical function that takes different *OUT* values from  $KL_l$  and  $\overline{KL_l}$  [70].

The characteristic function of the class  $KL_l$  will be represented as a function of the algebra of logic (Boolean function)  $F_{KL}$ , which is equal to zero (0) on the information descriptions of the  $sp_{an} = (\alpha p_{an1}, \dots, \alpha p_{anMI})$  object from  $KL_l$  and equal to one (1) on the remaining sets of indicators from  $E_{KL}^{MI}$ .

$E_{KL}^{MI}$  is the collection of sets with length  $r_{pa}$ . In this case, the  $KL_l$  class coverage is assigned a conjunction allowed for  $F_{KL}$ . And the dead-end coverage will correspond - the maximum for the  $F_{KL}$  conjunction. The admissible  $\mathfrak{R}$  in the matrices of indicators of objects will determine the belonging of a particular  $sp_{an} = (\alpha p_{an1}, \dots, \alpha p_{anMI})$  object to the  $(KL_l) = (B_{p_{al}})$  class if the condition  $(\alpha p_{a1}, \dots, \alpha p_{aMI}) \notin NI_{\mathfrak{R}}$  was met.

In our case, obtaining a reduced disjunctive normal form (RDNF) of a function is reduced to constructing a RDNF for  $F_{KL}$ , which takes the value 0 on the sets from  $B_{F_{KL}}$  and the value 1 on the remaining sets of  $E_{KL}^{MI}$ . After the RDNF for  $F_{KL}$  being obtained, it is necessary to remove the conjunctions  $\mathfrak{R}$  that do not have the property  $NI_{\mathfrak{R}} \cap A_{F_{KL}} \neq \emptyset$

For example, it is possible to construct an RDNF of a logical function by transforming a conjunctive function (CF) of the form:

$$D_1 \wedge D_2 \wedge \dots \wedge D_u, \tag{6}$$

where,

$$D_i = p_{ax1}^{\beta_{i1}} \vee p_{ax2}^{\beta_{i2}} \vee \dots \vee p_{axMI}^{\beta_{iMI}}, i = 1, 2, \dots, mu$$

implements function  $F_{KL}$ ,  $\beta_{iMI}$  - elements of the set  $B_{F_{KL}}$ .

Let one introduce the following notation –

$$p_{ax}^{\alpha} = \bigvee_{\beta_i \neq \alpha_i} p_{ax}^{\beta}. \tag{7}$$

Then the CF takes the form

$$D^*_{i1} \wedge D^*_{i2} \wedge \dots \wedge D^*_{iu}, \text{ where}$$

$$D^*_{i1} = \bigvee_{i \neq \beta_{i1}} p_{ax1}^{\eta} \vee \bigvee_{i \neq \beta_{i2}} p_{ax2}^{\eta} \vee \dots \vee \bigvee_{i \neq \beta_{iMI}} p_{axMI}^{\eta},$$

$$i = 1, 2, \dots, u.$$

Therefore, the construction of an EC for the simulated class of graphic primitives on the drawing documentation can be reduced to the subsequent implementation of the following steps:

- 1) set the characteristic function of a graphic primitive, for example, for a circle, this is the corresponding function that describes this circle, for a rectangle or square, the coordinates of the vertices, etc.;
- 2) find a reduced disjunctive normal form that implements the characteristic functions of the corresponding primitives located in the projection of the section of the corresponding object of recognition;
- 3) find an admissible (maximum) conjunction

$\mathfrak{R}$ , which determines whether the object belongs to the class of drawing primitives under consideration.

Let one analyze the case when objects from the PA set under study are described by indicators, each

of which takes values from the set  $\{0, 1, \dots, k_{p_i} - 1\}$ , i.e. in binary form, convenient for circuitry or software implementation of convolutional neural network.

One can assume that the classification of objects (i.e., graphic primitives used in drawing and construction documentation) is a set of potential variants of projection images inherent in a particular product range.

In the proposed convolutional neural network, each elementary classifiers will attribute each conditional square to a certain class of drawing primitives. At the CNN training stage, it is necessary to maximize the number of candidate regions that are involved in the process of recognizing primitives on drawing and technical documentation. Further, using the module with EC, the operation of compiling a map of objects is performed. Moreover, this map is compiled taking into account all the proposals for the primitives available in the database. Since the technical task of the software implementation of convolutional neural network is not set, at this stage of research, one of the open libraries, for example, PyTorch, can be used.

Most of the open libraries used for training convolutional neural networks are written in Python, so the implementation of a module that implements the solution of the problem, the classification of drawing primitives, into such a network can also be done in Python.

#### 4. CONCLUSIONS

As a result of the research the architecture of a convolutional neural network with a EC module of graphic primitives was proposed for solving the problem of recognition of drawings and transformation  $2D \rightarrow 3D$ . Moreover, a classifier model of graphic images based on class coverage and elementary classifiers of primitives was developed to improve the efficiency of convolutional neural network training performance. It was also shown that the paradigm of building a base of primitives for training convolutional neural network (or logical learning procedures - LLP) is to find informative fragments of descriptions of the corresponding graphical primitives. These fragments, when creating specific design solutions for recognition systems for drawing and construction documentation, for example, based on convolutional neural networks, will allow you to unambiguously conclude that there is (or is not) a certain graphic primitive within the class in the recognition system base. The basic principles of LPO design using the apparatus of logical functions are outlined, which will allow in practice to create effective convolutional neural network software solutions in the tasks of drawing recognition and  $2D \rightarrow 3D$  transformation.

Therefore we can safely assume that the main goal of this scientific research was completely achieved. Further researches in the field of  $2D \rightarrow 3D$  transformation will include more in-depth research on the graphical primitive detalization topic.

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