Forecasting and Management of the Process of Career Guidance Classification in Groups of Technical Specialties

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Abstract
This paper is devoted to the evaluation of the results of the introduction of the ColourUnique Pro career guidance software package into the process of career guidance support in control groups of subjects tested on the basis of the technical University. The peculiarity of the testing methodology used in the research is the generation by the subject of a unique color image that characterizes the individual style of activity. The types of personalities that are more common in creative and technical environments have been derived, which allows forecasting and management in the process of career guidance support of an individual. However, in a larger sample, a previously rarely encountered type of individual made itself felt, which was not previously considered characteristic of the technical environment, which may be erroneous. In the paper, the authors make the assumption that they can predict such images.

Keywords
Convolutional neural network, career guidance, classification of images, technical sciences, GraphiCon 2023.

1. Introduction

Today, career guidance is more important than ever to help young people in self-determination. Our world is overflowing with various sources of information, and the abundance of opportunities both provides limitless horizons for self-realization, and causes fatigue, confusion and indecision among so many options for work or study.

This research is devoted to automated career guidance testing, during which the subject generates a unique color image [1] that characterizes the style of his ISA [2]. Individual style of activity (ISA) is a system of distinctive features of a particular person's activity, due to his individual and personal characteristics. The involved ColourUnique Pro software package is considered as a decision support system [3], since a large number of applicants are required to undergo rapid testing, which would help them choose a University or, according to the results of rapid testing, undergo more in-depth career guidance diagnostics.

Testing was carried out in control groups of subjects considering a technical university as a future place to study, or already studying or working in a technical specialty. In total, 373 people in the following age categories were involved in the research: "less than 16 years old", "16 – 30 years old", "over 30 years old". The initial limitation of this testing method is considered to be the age range from 16 to 30 years, however, mass testing allowed us to evaluate the results also in control groups of middle school students, and not only high school students preparing for University admission.

Before starting the experiment, the authors hypothesized that in the control groups of subjects interested or already studying in a technical specialty, the dominant type of ISA would be A, then D, then C. Less than 10% percent will be types B and E, less than 5% or 0% will be type F.

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The purpose of the research is to verify the proposed assumption as a result of testing. To achieve the goal, the following research tasks were formed:

1. Conduct automated testing
2. Check the results of the classification performed by the neural network
3. Correct the results
4. Interpret the results and confirm or refute the proposed assumption

Testing was built in such a way (in accordance with the University's task) so that quickly, without dividing into subtypes, it was possible to understand which applicants are most suitable for an ISA for a technical university (presumably types A and D), and which ones should be considered creative directions (E and F).

Now, consider at the test results.

2. Testing features

Many modern testing methods, and such classic tests as the well-known Holland test, involve a choice of several answer options, while as a result of working with ColourUnique Pro, a unique answer is created in the form of an image. Nevertheless, within the framework of this methodology, 6 main types of ISAs have been identified to date. This is due to the initial structure of the quasi-space, which the subject fills with color (figure 1).

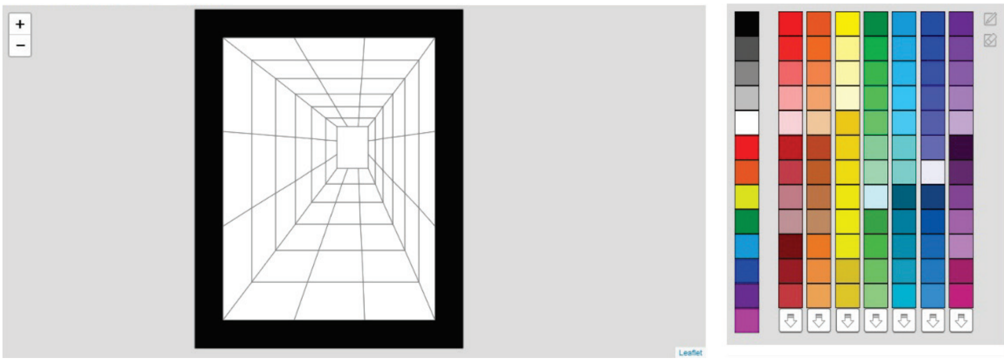


Figure 1: Quasi-space to fill with color

It has a cellular structure, which allows you to isolate only 4 types of elements – further indivisible, the smallest fragments of texture. These are "horizontal lines", "vertical lines", "chess" and "gradients", we can see them on figure 2.

There are only four groups of elements, and six types of individuals, since type C implies the presence of "gradients" and "vertical lines" at the same time, and type F is a fragmentation of the original quasi-space grid (figure 3). Type A contains the elements "horizontal lines" as dominant, type B – "vertical lines as dominant, type C – a combination of "horizontal lines" and "gradients", type D – "chess" and "chess-like" elements as dominant, type E – "gradients and a relatively large number of colors and shades. Type A is more common among people of technical specialties, while type E is more common among creative people. Type D is currently approximately equally distributed in both technical and creative environments.

Using the term "texture", the authors mean sweeps of images – planar representations of quasi-spaces, which are subsequently analyzed by a neural network. Since words such as "space" and "corridor" sound in the task for the subject, implying the presence of image depth, the subject should see the effect of perspective deepening in front of him [4]. The quasi-space must also be asymmetric, since a symmetrical space, even with the effect of perspective distortion, is perceived more flatly than an asymmetric one [5].

Why sweep is more preferable for a neural network? The fact is that perspective distortions contribute to the uneven perception of cells and elements that are formed by their special combinations. Sweeps allow you to represent textures consisting of equivalent square cells, as in figure 4. The presence of perspective distortions makes the cells unequal, creates the illusion of planning, where distant cells look small or even mixed (figure 5).

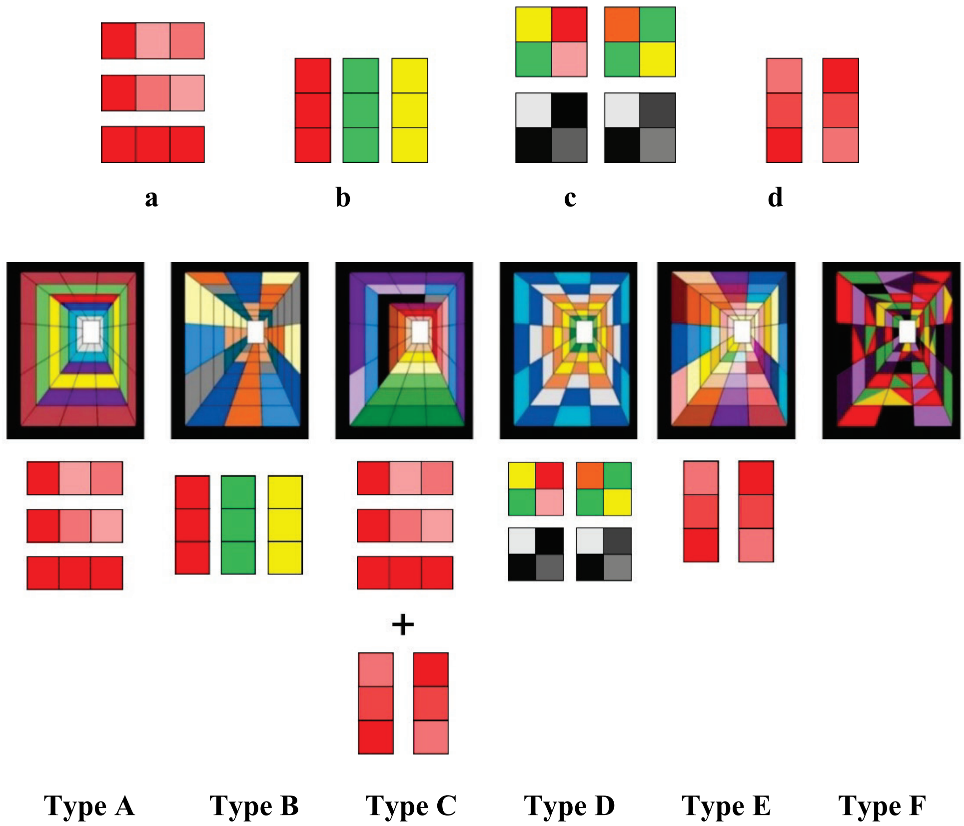


Figure 2: Texture elements: a – "horizontal lines", b – "vertical lines", c – "chess", d – "gradients", and types from A to F

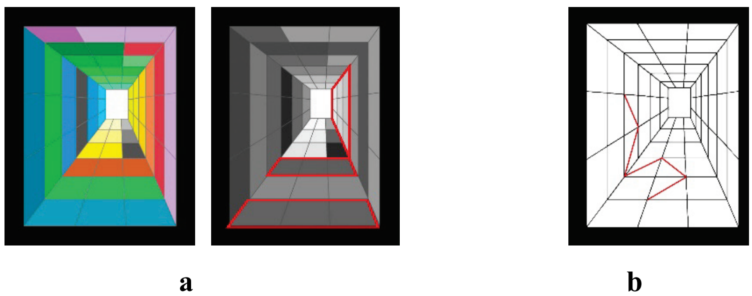
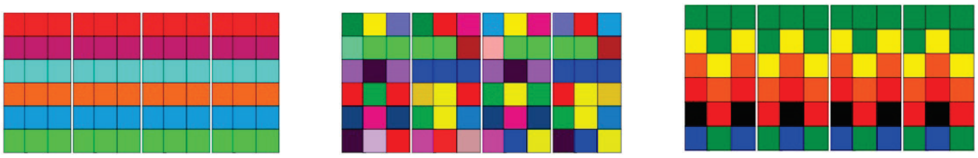


Figure 3: Image classes: a – class C with the elements "horizontal lines" and "gradients", b – class F, with additional divisions of the original quasi-space grid

There are several definitions of the concept of "texture", as well as methods for determining them [6 – 8]. In this study, "texture" is understood as an image surface (planigon) organized in a certain way (through combinations and repetitions of geometrically correct elements) [9, 10]. Due to the fact that the quasi-space is initially a cellular structure, the images obtained for analysis (sweep) at the moment do not need segmentation to determine clearer edges of the target objects (selected elements), since the boundaries for them are already marked.

However, the neural network confuses some elements that are similar to each other, which is probably the reason for using some additional segmentation methods. For example, contrast enhancement.

The technical University, on the basis of which the study was conducted, was interested in a faster and simpler version of ColourUnique Pro, which could help quickly determine the type of ISA (without dividing into subtypes) and help the student understand whether training in technical specialties (types A and D) is suitable for him. To do this, it was decided to use only a neural network classifier built on the basis of the convolutional neural network Inception v3 [11]. A total of 1915 images were processed, of which 1530 images were used for network training, 385 for experiments. Before the start of the network training, images were collected, performed by live people according to the task of the test, but their number was not enough for training, and therefore it was decided to apply some augmentation methods, namely, 180-degree rotations. Due to the specificity of the task, some augmentation methods, such as stretching, rotations by degrees other than 180, curvature, and others were not used, as this would lead to distortion of the sweep. So the number of images was increased from less than 500 to 1915. Initially, the choice of a neural network as the basis of one of the classifiers was due to the presence of entire classes of objects, where the sets of parameters differ, or not all parameters are found in all classes. Simple at first glance images and geometrically clear elements eventually represent quite complex objects for classification. Both for an expert (human) and for a machine.



a **b** **c**

Figure 4: Sweeps of quasi-spatial images

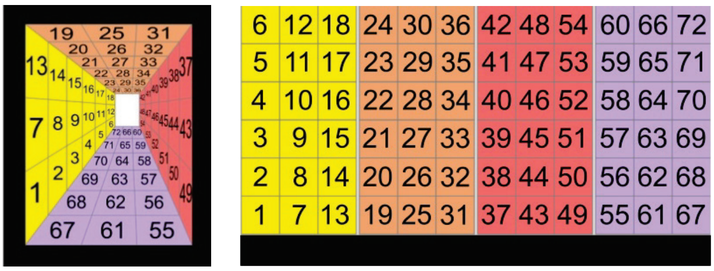


Figure 5: Perspective distortions of cells in quasi-space

Convolutional neural networks (CNN), in particular – Inception v3, are widely used to classify images in various fields of human activity, from fashion to medicine [12 – 15]. This architecture served as the basis, then 5 fully connected layers were attached to it. The first layer has 64 neurons, the second has 32 neurons, followed by the dropout layer, which is responsible for preventing retraining. Stochastic gradient descent (SGD) was used as an optimizer. Python, Jupyter Notebook, TensorFlow, Keras, OpenCV and NodeJS were also used as additional tools.

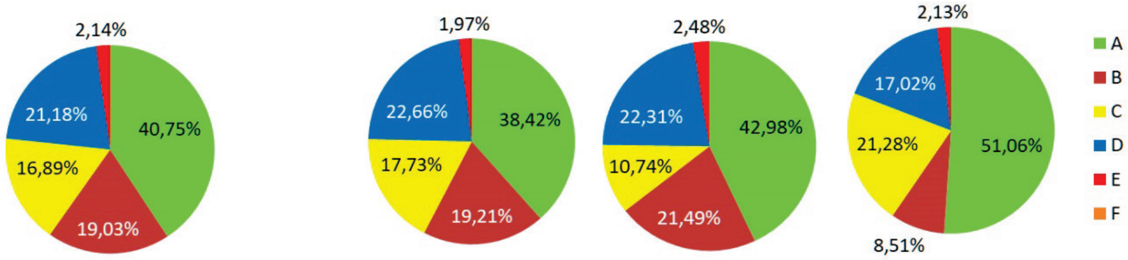
3. Analysis of the results

373 people took part in the research. The evaluation of the results took place in four stages:

1. Analyze the distribution by type after the machine classification of images
2. Make adjustments with the help of an expert (human)
3. Analyze the distribution by type after expert adjustment
4. To assess the validity of the assumption regarding the distribution of types in the control groups of subjects of technical specialties

Figure 6 shows diagrams of distribution by type after stage 1, that is, after classification by a neural network.

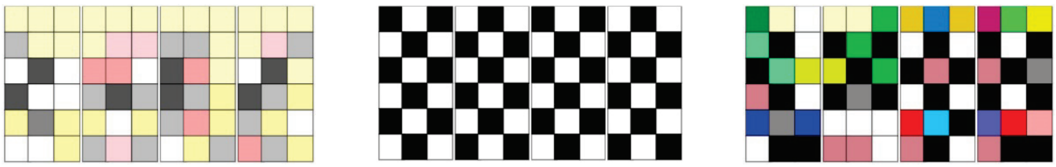
Since there were very few people in the "over 30" category (less than 10), it was decided not to take this category into account when analyzing the results. Since most people go to University after school or college, the groups of "16 – 19 years old", as well as schoolchildren (under 16 years old), were of the greatest interest, since previously this group was not sufficiently studied in relation to the distribution of ISA and the dependence of this distribution on the bias or specialization of the school.



a **b** **c** **d**

Figure 6: Distribution by type after machine classification: a – all tested, b – age group "under 16" (203 number of people), c – age group "16-19" (121 number of people), d – age group "20-25"

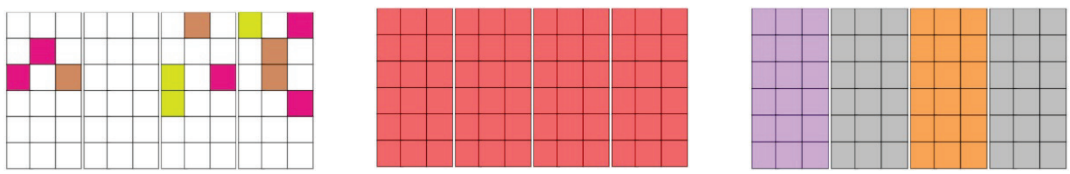
Stage 2 of the analysis of the test results consisted of an expert checking the results of machine classification, detecting network errors and incorrectly filled out forms. This question is of particular interest at this stage, since what in theory can be considered an incorrect or incomplete form can also be regarded as a feature of filling out the form, that is, a variant of the correct form. For example, in Class D "chess" images, it is not uncommon for subjects to use white cells to create "chess" or "chess-like" structures (figure 7):



a **b** **c**

Figure 7: Examples of images belonging to Class D are "chess", where subjects use white cells to form characteristic elements

If you look at the example figure 7, b, you can see that the subject left half of the cells of the field "empty" – white, which, nevertheless, allowed to obtain a bright and characteristic texture. Such examples are rare, but they occur and cannot be considered an "incorrect form" of filling out the test. However, with respect to type B images, half of the empty cells cannot be considered a structure, since it rather forms the background. In theory, the entire form filled with one color (the same RGB coordinates) can be considered a Class B image, serve as an example of a special self-expression. Can such self-expression be considered "incorrect"? Figure 8 shows several examples of such images.



a **b** **c**

Figure 8: Examples of images belonging to Class B: a, b are examples of supposedly "incorrect forms", c is an example of a correct form using at least 3 colors

Considering the example of figure 7, b, it becomes obvious that in order to increase the accuracy of testing, it is necessary to introduce an additional rule for the subjects when filling in, for example, to use at least 3 colors. Thus, it is possible to obtain the simplest variations of all 4 types of elements and exclude accidental sending of empty forms and filling of quasi-space with one color (the same RGB coordinates).

After filtering out incorrect forms and detecting network errors, the results were obtained, which you can observe on figure 9 and figure 10.

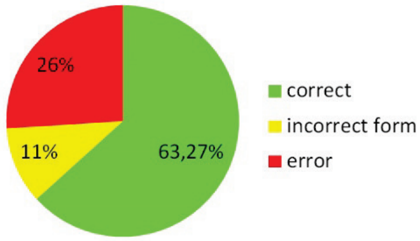
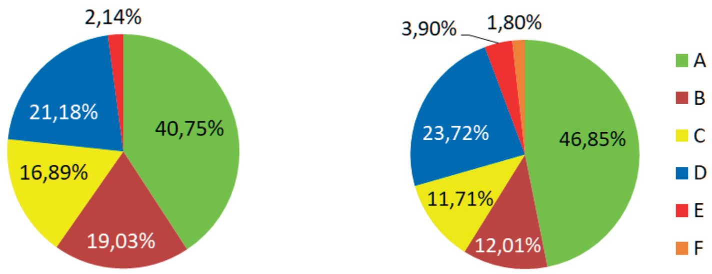


Figure 9: Diagram of the accuracy of machine classification after verification by an expert and taking into account "incorrect forms"



a **b**

Figure 10: ISA type distribution diagram: a - machine classification; b - machine+expert classification ("incorrect forms" are excluded)

After adjusting the machine classification (stage 3), the percentage of Class B images decreased from 19 to 12%, which still makes it quite high, given that previously this type was considered more "creative" than "technical" and was conventionally called "moderately avant–garde" [16 – 18]. At the moment, the neural network "confuses" the elements of "vertical lines" with "horizontal" or "gradients". The latter contain cells of the same tones but different color coordinates in the 3x1 definition area, while in order to be considered a "vertical line", an element in the 3x1 definition area must contain cells of strictly identical RGB color coordinates.

The assumption put forward before testing is confirmed by the fact (stage 4) that, in general, type A is indeed the most pronounced in groups interested in the technical direction – 47% of the subjects (156 number of people). In second place is type D, 24% (79 number of people). Type E was also less than 10%, namely 4% (13 number of people). The least pronounced type F is about 2% (6 number of people). However, as a percentage, type B exceeded the predicted value (it was 12% instead of 10 or less) and exceeded the number of C images.

Let's compare the severity of type B as a percentage with the group of subjects of "creative directions" in the age range of 16 –19 years (80 number of people) (figure 11). Since there are usually fewer places in academic groups of "creative directions" than in technical ones, the sample of subjects is smaller.

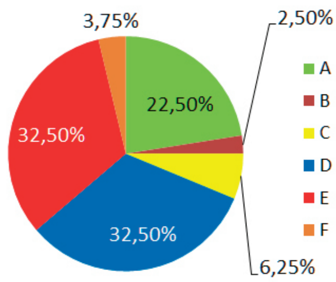


Figure 11: ISA type distribution diagram in groups of "creative" directions

Nevertheless, it is already clear that in such groups the percentage of type E severity is much higher. Also, type D is often not clean there, as in figure 7, b or c. There are often variants with a higher number of shades, as in figure 12.

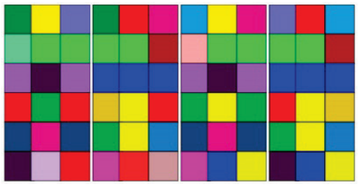
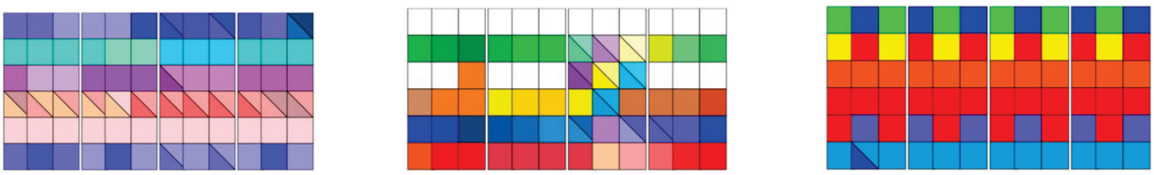


Figure 12: Subtype D approaching E

The analysis of the test results posed the following questions to the author's team for further development of the study, such as:

1. Study of type B and its severity in different groups of subjects, not only "technical" and "creative" (of particular interest is a hypothetical large-scale study of the severity of all types in large control groups of representatives of various fields of activity)
2. Correction of the rules for filling out the test
3. Identification of clear signs of "incorrect form" that could be classified as a separate class
4. The selection of more "strong" or "significant" elements that play a decisive role in determining the type
5. Study of the distribution of ISA in the age groups "under 16" and "over 30", since the development of the brain is not the same in different periods of human life, which can serve as a basis for research on the peculiarities of human perception and confirm (refute) the validity of the age limit for testing from 16 to 30 years

Explaining paragraphs 4 and 5, it should be mentioned that in the studied textures, the expression of the elements varies from individual to individual. Someone prefers bright and contrasting colors, someone – more "deaf" and nuanced, also with elements. Some images can be classified without the help of machine vision, and some images are dominated by elements that turn out to be piece-by-piece, but more contrastingly highlighted, while in fact other elements that "hide" behind a nuanced color scheme may prevail. Their role in the definition of ISA is currently being studied, in the future they can be defined as characteristic objects [19, 20], while areas that do not contain the desired elements at all can be considered a "background" [21]. Also, analyzing the results of testing in groups of "technical" specialties, the important role of hierarchy among the attributes becomes obvious. Let's consider it on the example of images containing elements of class F (figure 13).



a **b** **c**

Figure 13: Images with signs of class F (additional cell divisions: a - in all quarters, b - localized, c - single, possibly random

Earlier, the author of the methodology was of the opinion that if the subject used the "cut" tool, then this already indicates the dominance of type F. Initially, the tool is built into the user interface in such a way as not to attract attention. And if the subject was deliberately looking for an opportunity to transform the original grid, is this intention enough to attribute it to type F? Using the example of figure 13 a, b, we can see a meaningful application of the "divide" function, since in the case of a, the separated cells are distributed along lines with concentration to the center of the image, in the case of b, they are collected from one of the quarters. If we look at option c, we can assume that a single cut is "random", while "horizontal lines" of shades of red and bright blue cells forming the outlines of a "chess-like" structure look much more contrasting and "demonstrative". Undoubtedly, the separated cells make the F-type images strikingly different from the others. Nevertheless, even if the separated cells are singled out as a more "strong" and "defining" feature, then it is necessary to allocate a minimum number of separated cells that could overlap other elements in weight and importance.

A similar question concerns the "vertical lines" elements. At the moment, the presence of three such elements in the scan is sufficient to determine the dominant type B. But can "vertical lines" be considered such a "strong" sign? Since "vertical lines" can be surrounded by both a small number of colors and pronounced other elements, and vice versa (figure 14).

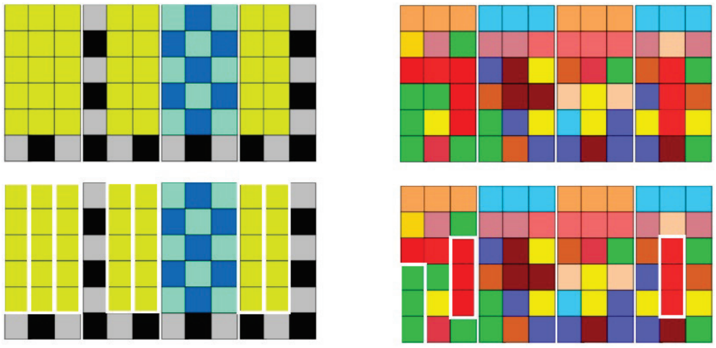


Figure 14: Images with signs of class B

And finally, the need to work in groups "over 30". This group should also be divided into subgroups, such as "30 – 39 years old", "40 – 49 years old", "50 – 59 years old" and "over 60", since the psychology and physiology of the brain differ at different ages. The influence of the individual's life experience and his level of critical thinking on the search for a solution to the task is not the same. So, among people over 30 years old, the question "is it possible to cut the cells" often sounds, while young subjects (16 – 19 years old) often simply perform the task – to color the quasi-space with colors from the proposed palette and are almost not interested in the possibility of additional cell separation.

The solution of these new tasks will help enrich the process of career guidance testing, make diagnostics more in-depth and individualized. And, at the same time, since career guidance concerns working with people and accompanying them in one of the most important life choices – profession and purpose, it is impossible to completely exclude an expert from this process as an empathic person and a person exercising control over the process of machine classification of individuals. In any case, this is impossible with detailed diagnostics, which follows a quick primary test using only a neural network.

As a conclusion, it is noted that all the tasks set before testing were solved, in particular:

1. Automated testing was carried out
2. The results of the classification carried out by the neural network are verified
3. The results are corrected by an expert
4. The results have been interpreted, some of the assumptions made before testing have been confirmed, some have been refuted
5. The new tasks of this study are outlined

Testing has shown that the most common among young people who want to get a "technical" specialty are indeed types A and D, which makes it possible to predict the distribution of ISA when working with groups from different schools, as well as to manage career guidance processes in schools and Universities.

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