Providing Decision Support in Career Guidance Through the use of Machine Vision

Iuliia Tarasova[1], Vyacheslav Andreev[2], Andrey Chechin[1] and Denis Toskin[2]

[1] *Nizhny Novgorod State University of Architecture and Civil Engineering, Ilinskaya str., 65, Nizhny Novgorod, 603950, Russia*
[2] *Nizhny Novgorod state technical university n. a. R. E. Alekseev, Minina str., 24, Nizhniy Novgorod, 603950, Russia*

Abstract

This paper is devoted to the review of the results of the development and implementation of the ColorUnique Pro career guidance software package in the career guidance activities of higher educational institutions. The review begins with the initial formulation of the problem, justification of the use of neural networks as the basis of one of the classifiers, consideration of the results of experiments and then – the introduction of a software package. At the end of the article, prospects for further research are described, such as the creation of a three-dimensional map of types and subtypes and the further identification of new subtypes. The possibility of using additional methods of analysis, detection and classification is also being considered in order to study the influence on the definition of ISA of such features of the images obtained as «demonstrative» and «true» structures, as well as the presence of a «background» that does not contain characteristic elements. In addition to neural networks, the authors also used the «sliding» window image processing method, as a result, the software package includes two classifiers that analyze images separately, however, in the future, the results of the analysis of both classifiers are compared by an expert, since some subtypes can only be determined by joint interpretation.

Keywords

GraphiCon 2022, computer vision, neural network, sliding window, software package.

1. Introduction

Today, information technologies have not bypassed career guidance, in particular, specialized software systems are used, for example, Effecton, designed to support the user in a situation that presents moderate and sometimes significant difficulties. Professional self–determination is a complex and lengthy process in itself, it is even more difficult in a situation of an abundance of options and insufficient vocational guidance during school years.

Also, a significant role in this difficult process is played by a human expert who provides support for the decision–making process both individually and jointly with the use of one of the career guidance software complexes. Since professional guidance methods and software complexes are computer programs that generate solutions for the user (the decision-maker), they can be considered decision support systems [1].

In accordance with the requirements and demands of modernity, career guidance methods are automated and updated, as well as new ones are being developed. The basis of the ColorUnique Pro software package, which will be discussed further, is the «Associative Color Space»© testing methodology, which involves user diagnostics using ISA [2], and the user's response is not to choose the preferred option from the proposed program, but to generate their own, unique quasi-spatial image [3]. When automating such a technique, the human factor is especially obvious in the form of expert errors committed due to the individual characteristics of the perception of the expert himself, his

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EMAIL: tar06@list.ru (I. Tarasova); vyach.andreev@mail.ru (V. Andreev); chechin-a@yandex.ru (A. Chechin), toskin.dv@gmail.com (D. Toskin)
ORCID: 0000-0003-4770-9431 (I. Tarasova); 0000-0002-7557-352X (V. Andreev); 0000-0001-8038-9404 (A. Chechin) 0000-0002-8083-8617 (D. Toskin)

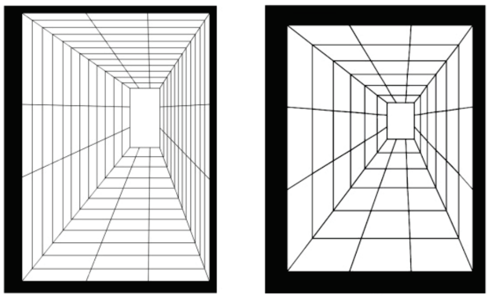
personality, susceptibility to external stimuli, as well as previous visual experience and life experience in general. All this affects the perception of even the simplest visual information, it can be completely different for different people [4].

For the most effective career guidance diagnostics, a person (expert) should in no case be excluded from the decision-making support process, since a person is able to compare the test results with the previously noticed features of the subject, however, expert errors can lead to undesirable consequences.

Thus, the ColourUnique Pro software package was created to help the subject and the expert in the process of career guidance diagnostics, namely, to reduce the number of errors and identify image elements that are not visually detectable by the human eye. A person is still irreplaceable in social systems, but his joint work with the software package allows for the most complete and individual diagnostics.

2. The analysis of quasi-spatial images

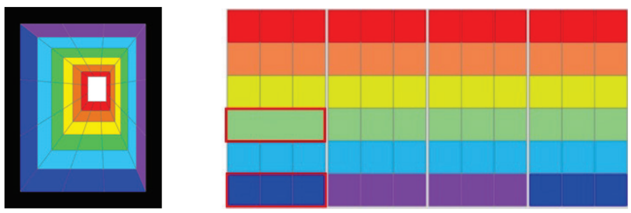
The object of research is quasi-spatial images obtained as a result of user interaction with the interface of the software package. The user himself sees a pseudo-space as a field for drawing, while the software package analyzes a scan that does not have a perspective distortion. This is due to the fact that in the task for the subject, words such as «space» and «corridor» sound, implying the presence of image depth. Therefore, for the best understanding of his task, the subject should see a corridor or a space in front of him, necessarily somewhat asymmetric, since a symmetrical space, even with the effect of perspective distortion, is perceived more flatly than an asymmetric one (Figure **1**, a and b), [5].



a b

Figure 1: The test form of the quasi–space: a - initial, b – simplified

An example of the finished test form and its unfolding is shown in Figure 2, a and b:



a b

Figure 2: Ready-made test form: a - quasi-space, b – scan

The ColourUnique Pro software package, created for the purpose of analyzing and classifying quasi-spatial images for career guidance, has the following structure (Figure 3).

1. **ColourUnique M**, where M is monitoring. The first part of the program, which collects and systematizes data about the user (age, gender, occupation, education level), and also automates the process of filling out the test form. Finished forms are still being evaluated by a teacher or psychologist (expert).
2. **ColourUnique A**, where A is an analysis. This program already includes a number of algorithms for correlating test forms with derived types of individuals, the process is controlled by

a person (an expert) who evaluates the correctness of the program, and also provides the developer with information about errors, if any.

3. **ColourUnique R**, where R is the result. At this stage, the program automatically generates detailed recommendations and outputs the test result in a PDF file available for download on a PC or smartphone. The task of a person (expert) is to evaluate the correctness of recommendations, their volume and ease of downloading, as well as the convenience of reading a file from a PC or smartphone screen.

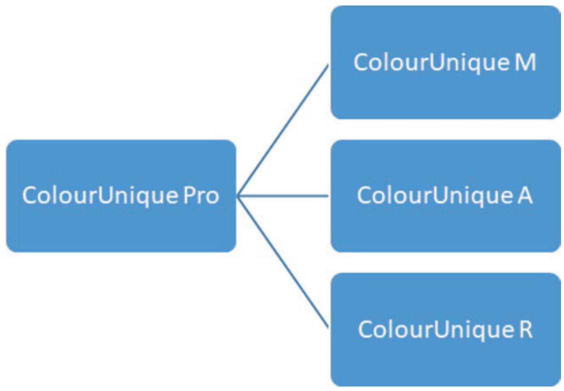


Figure 3: The structure of the Color Unique Pro software package

2.1. Second level heading

Initially, the formulation of the research task sounded like this.

Suppose that there is a set of different quasi-spaces obtained as a result of experiments conducted with the participation of subjects X_m, m=1, ... , n. For the purpose of conducting research, a sample is made from this set Y_k, $50 \leq k < n$. It is required to define a sequence of actions that allows classifying each object of this sample for belonging to a certain class (A, B, C, D, E, F), (Figure 4).

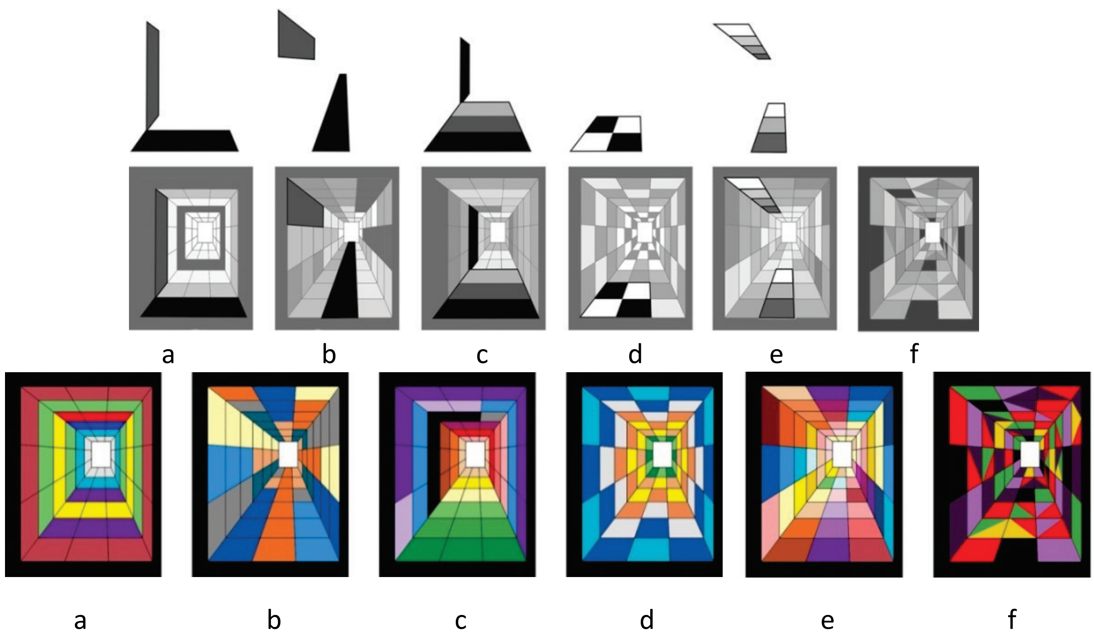


Figure 4: Derived types of individuals: a – type A, b – type B, c – type C, d – type D, e – type E, f – type F

However, in the process of working with control groups of subjects and building classifiers, it became obvious that the task is much more difficult than determining the presence of certain signs of the desired classes in the image. In most quasi-spaces, the signs are mixed with each other and also form a number of characteristic combinations, which allows us to judge the presence of features of types and a number of subtypes that also have their own characteristics. These features cannot be described by a short formula, but require the use of a computer in combination with an expert (human) assessment.

All of the above shows the complexity of classification tasks in this case, forcing us to look for other ways to solve the problem. One of these methods is the use of a complex of classification algorithms, which includes neural network algorithms and a «sliding» window image processing algorithm.

For example, by the «sliding» window, it is possible to distinguish the features of the desired classes, while neural networks consist of elements similar to elementary brain functions, that is, they are able to demonstrate some properties inherent in the human brain (the ability to learn, generalize experience, extract essential properties from incoming data, cutting off unnecessary data) [6, 7].

2.2. Experiments with a neural network

To implement the first classifier (part of ColourUnique A), three convolutional neural network architectures were used: MobileNet [8], Inception_v3 [9] and U-net [10]. A total of **1915** images were processed, of which **1530** images were used for network training, **385** for experiments.

The accuracy indicators of the networks after training and testing on a test sample are shown in Table 1.

Table 1
The accuracy of classification of three network architectures

Inception_v3	MobileNet	U-net
91,12 %	84,51%	71,05%

Next, experiments will be described for a classifier built on the basis of the Inception_v3 network architecture.

Three tests were conducted to evaluate the effectiveness of the neural network classifier. In all three experiments, the number of images for each class was the same (25 images per class for tests 1 and 2, 10 images per class for Test 3). Since quasi-spatial images belonging to classes B and C are much rarer than images belonging to classes A, D and E, it was decided to apply augmentation to the number of images of classes B and C that could be obtained from «live» subjects in experiments 1 and 2. During experiment 3, all images were obtained from «live» subjects.

The age of the participants ranged from 17 to 28 years, among them 45% were men, 55% were women. Interpretation of results:

- ***Correct*** – the coincidence of the expert's opinion and the result of the network classification.
- ***Network error*** – the classifier names the wrong class (the signs of the named class are either absent or present in small quantities in comparison with others).
- ***Expert error*** – the expert assigns the wrong class to the image, or places the scan in a folder with the correct class, but in his list marks another class as the most likely for this scan.

Test 1. The number of images for the test: 150 (25 images per class). A classifier based on the Inception_v3 network architecture. Expert: developer of the testing methodology.

Test results 1 (Figure 5):

1. The highest percentage of correct answers was found in Class E (65%), the lowest – in class D (35%).
2. The highest percentage of expert errors was detected in Class C (65%), the lowest – in class D (10%).
3. The accuracy of the network, taking into account the expert's error by class, was: A – 64%, B – 70%, C – 75%, D – 45%, E – 65%.
4. The overall accuracy of the network was 63.8%.

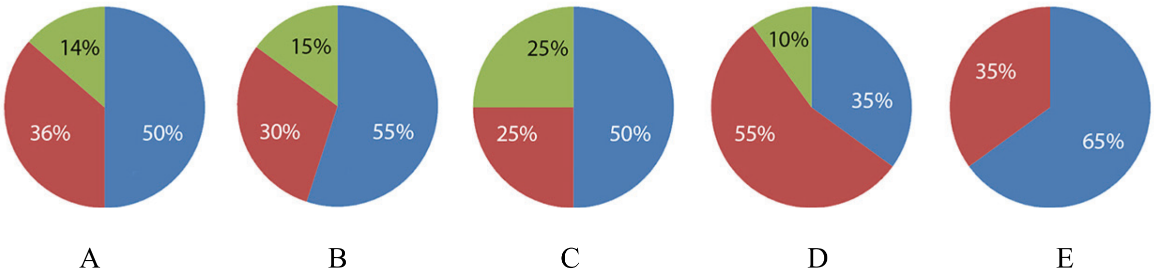


Figure 5: Diagrams of the test sample of the scans with the attributes of the desired classes. Blue is correct, red is a network error, green is an expert error

Test 2. Number of images for the test: 150 (25 images per class). A classifier based on the Inception_v3 network architecture. In this test sample there were «bright» (visually detectable) and somniferous (visually heterogeneous) samples in the ratio of 50/50. Expert: developer of testing methodology.

Test results 2 (Figure 6, Figure 7):

1. In a sample of samples with heterogeneity of features: the largest percentage of correct answers was found in class B (80%), the smallest - D (69%).
2. In a sample of samples with visually detectable features: the highest accuracy of the network was found in class A (100%), the lowest – In (75%) and C (75%).
3. The expert error is highest in class C (50%), least – D (8%).
4. The accuracy of the network, taking into account the expert error by class, was: samples with heterogeneity of features: A – 83%, B – 80%, C – 75%, D – 69%, E – 73%; samples with visually detectable signs: A – 100%, B – 75%, C – 75%, D – 87%, E – 80%.
5. The overall accuracy of the network was 80%.

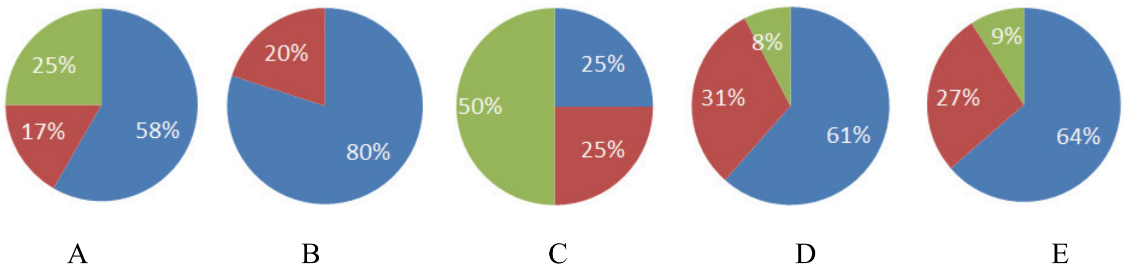


Figure 6: Diagrams of the test sample of the scans with the attributes of the desired classes. Blue is correct, red is a network error, green is an expert error

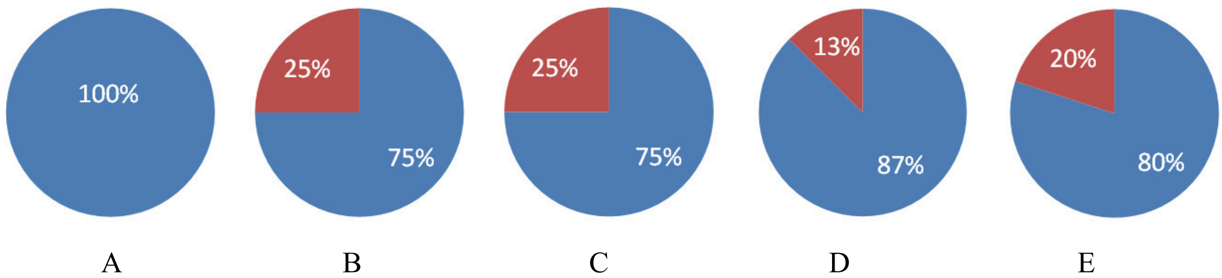


Figure 7: Test sample diagrams with visually identifiable classes. Blue is correct, red is a network error, green is an expert error

Test 3. Number of images for the test: 50 (10 images per class). A classifier based on the Inception_v3 network architecture. In this test sample there were «bright» (visually detectable) and questionable (visually heterogeneous) samples in the ratio of 50/50. Experts: developer of testing methodology, teacher of the group of subjects, psychologist.

Test results 3 (Figure 8):

1. The percentage of correct answers was 71%.
2. The percentage of network errors was 15%.
3. The percentage of expert errors was 14%.
4. The overall accuracy of the network was 85%.

Well, according to the results of tests 1, 2 and 3, it can be seen that the number of correct answers of the classifier increases, the number of errors decreases, while the number of expert errors increases at the time of test 2 and decreases again on test 3 (Figure 9).

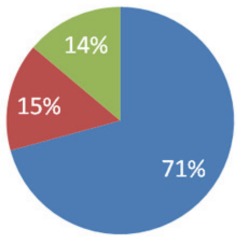


Figure 8: Test sample diagram. Blue is correct, red is a network error

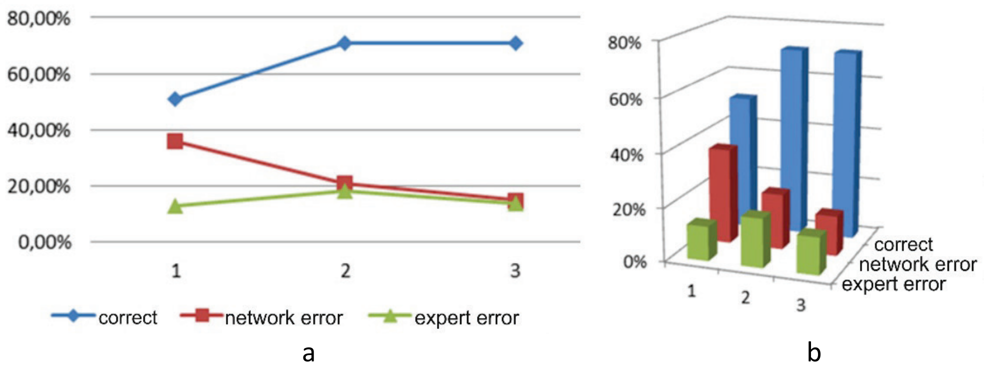


Figure 9: The graph (a) and histogram (b) of the dynamics of classification accuracy between tests 1, 2 and 3

Thus, the first classifier has a discrepancy between the predicted accuracy (91.12%) and the actual accuracy (80-85%), equal to 6-11% (5% is due to the difficulty of interpretation by the expert of the result of machine analysis).

2.3. «Sliding» window

Using the «sliding» window image processing method, the second classifier (part of ColourUnique A) was implemented, especially effective for analyzing Class C images, as well as separating subtypes of Class C and E images [11-12]. To evaluate the «chess» and «chess-like» structures characteristic of Class C images, several filters were implemented (Figure 10):

Also, by comparing the classification results through a neural network and a «sliding» window, it became possible to distinguish visually similar subtypes of classes C and E (Figure 11), which was previously not allowed by the neural network and visual classification carried out by an expert.

So, if up to 45% of class D structures are present in the image, but the neural network defines the image as class E, then we have a «non–contrast» subtype E (E1), if the neural network refers the image to class D, we have type D [15].

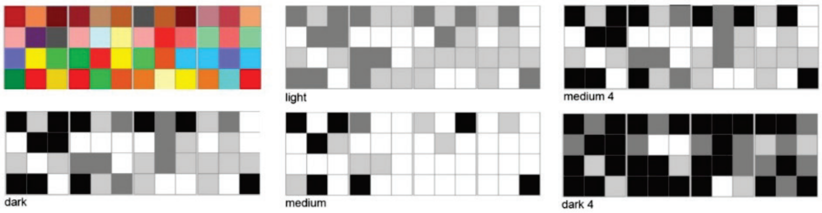


Figure 10: Identification of the desired structures in different areas of the planigon [13-14]

a b

Figure 11: The separation process of types and subtypes: a – class E images of the «non–contrast» subtype, b - class D images with hidden features of Class E

Well, the second classifier allows you to divide types according to the selected characteristics, with the joint interpretation of the results of both classifiers, it is possible to separate types and subtypes, taking into account the implicit structures and heterogeneity of the features of the desired classes, as well as individualization of the results by determining the proximity of the image to the group of types whose features are present in its structure.

2.4. Features of the program architecture

The created architecture of the decision-making process management system makes it possible to interact with the software complex both via a local network (school or university) and remotely (Internet), to carry out mutual verification of the test results by a person and a computer, which reduces the number of network and expert errors, while maintaining an individual approach to the career guidance diagnosis of the subject (Figure 12).

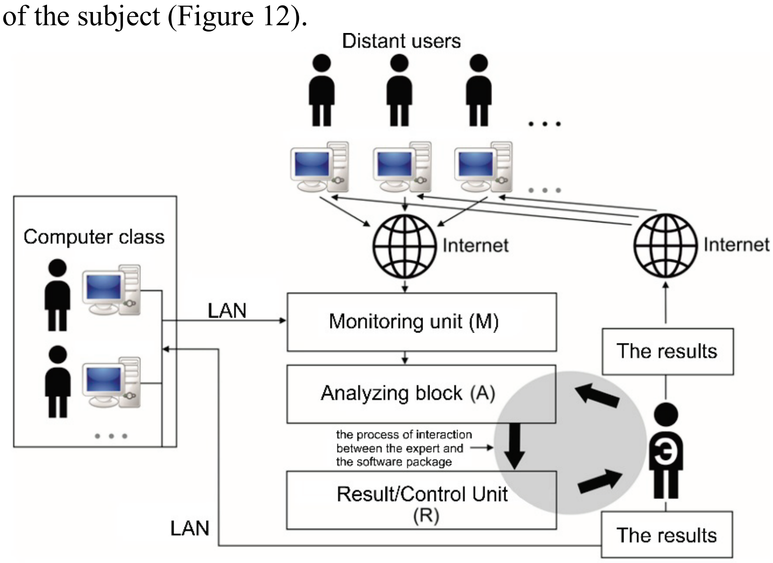


Figure 12: The architecture of the decision-making process management system through the ColourUnique Pro software package

3. Implementation results

The main applied results of the research are the results of the implementation of the developed software package in career guidance activities of higher educational institutions. Today it is possible to summarize the work in groups of «creative directions», in particular, designers, and technical directions - mathematicians, physicists, surveyors, programmers, etc.

In the process of implementing the results of the research, a group of applicants who consider any direction of the specialty «Design» as a future profession was tested (2021-2022 years of research). It was assumed that in the designers group, most of the subjects would make images that would belong to classes C, D and E, less likely - B and F.

Analysis of the obtained quasi-spatial images showed the following (Figure 13):

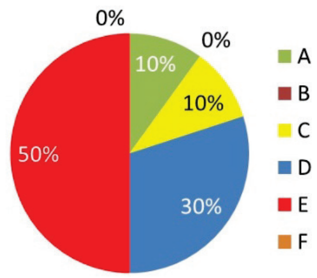


Figure 13: Diagram of the distribution of types of ISA in a group of subjects considering any direction of the specialty «Design» as a future profession

Well, the dominant types in the group of applicants considering any direction of the specialty «Design» as a future profession were types D and E.

Earlier, when testing first-year students who have already enrolled in the direction of «industrial design», it was noticed that types D and E are more common and also master the course program more successfully, in connection with which the author of the testing methodology «Associative Color Space» © suggested that individuals will also prevail among the most successful graduates of the course with an ISA type E or D. Statistics on those who have completed the course will be discussed further.

A similar study was conducted for subjects studying or planning to study in technical specialties (2021-2022 years of research). It was assumed that mostly the subjects would belong to classes A or D. The distribution by ISA occurred as follows.

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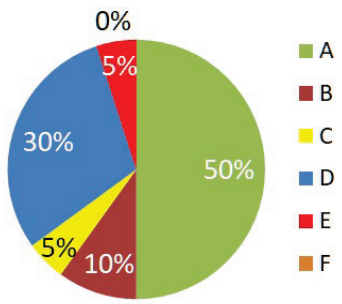

Figure 14: Diagram of the distribution of ISA types in a group of subjects studying in technical specialties (geodesy, mathematics, physics)

Thus, the dominant types in the group of subjects studying or planning to study in technical specialties were types A and D.

As for the characteristics of the number of colors used, there is also a certain pattern between the types. To determine it, a wide group of subjects was selected, among which all types were present, except for the rarely occurring B and F. For drawing up a graph and a heat map, a «window» of 105 subjects was designated, since representatives of type A turned out to be more than others (Figure 15).

Thus, representatives of types A and C use the smallest number of shades (on average from 5 to 25 shades), followed by type D (representatives of the D1 subtype using many shades, like representatives of type E, can mix up to 40 shades), and most of all shades are observed among representatives of type E – up to 60 shades (Figure 16).

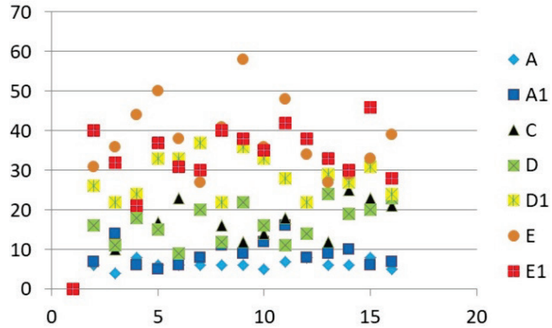

Figure 15: The graph of the distribution of types by the number of shades used

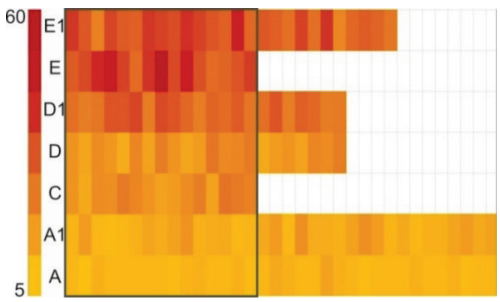

Figure 16: Heat map of the distribution of types by the number of shades used. The frame highlights an area of the same number of all types and subtypes in the test sample

Consider the statistics regarding graduates of the «Design» training course with the «industrial design» training profile for 5 years, starting from the 2018 graduation. The diagram shows the distribution by type of ISA among graduates who have defended their final qualifying work with an excellent grade, as well as having a commendation of the commission, a recommendation for further study in master's/postgraduate studies and/or a recommendation to submit a work for a competition or publication.

Of the 27 graduates marked on the diagram, all 27 were employed in a field related to design in one way or another (industrial design, game design, interior design, graphic design, art design, etc.).

This statistic partially correlates with the hypothesis of the methodology developer that among those who chose the «Design» direction, individuals with types C, D, E will receive the greatest representation (representatives of types D and E have the greatest representation). It was also fair to assume that representatives of types D and E would be the most productive and successful (33% and 41% among those who presented excellent final qualifying papers) (Figure 17).

Today, the authors are preparing to conduct a five-year study of groups of students of technical fields (mathematics, physics, geodesy, etc.) in order to predict the prevailing types of individuals on the ISA among the enrolled and prevailing types of individuals on the ISA among graduates with the best final qualifying works and successful employment in the specialty.

General conclusions of the research:

1. The improvement of the testing process and the collection of information about the subject has significantly reduced the amount of time spent on working with the test form (it was 3 hours manually, it became 20-30 minutes on the computer).

2. The methodology can be completed online, which means that the circle of its consumers has significantly expanded.
3. The accuracy of the network for the third test was increased by changing the initial optimizer, creating additional classification layers, and reducing the step of weights.
4. It became possible to machine separate visually similar subtypes E and D by comparing the results of two classifiers, which is impossible for an expert to accurately determine visually or using only one of the two classifiers, since these subtypes have features mixed in a specific way, for the network the types also look similar.
5. The testing has been successfully implemented into the educational process of design groups, allows you to predict the progress of students, implement an individual approach, and support the employment process.

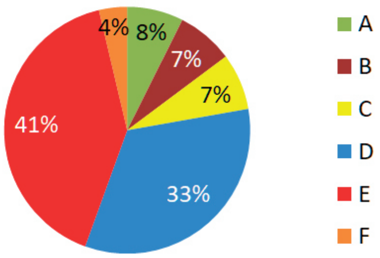

Figure 17: A diagram of the distribution of ISA types among graduates of the Industrial Design direction who defended their final qualifying work with an excellent grade

4. Research prospects

Despite the fact that the two implemented classifiers effectively separate the already derived types of individuals according to ISA, a number of tasks were formed during the study that also require analysis and solution, which will entail the study and testing of other methods of analysis, detection and classification when working with scans.

The following tasks are of the greatest interest:

1. Identification of «true» and «demonstrative» structures in the images obtained during the interaction of the subject with the ColorUnique Pro software package.
2. Separation of the «background» (areas that do not contain important elements) from the elements identified and designated by the author of the testing methodology as «characteristic».
3. Construction of a three-dimensional map of types and subtypes in order to most accurately determine the location of the subject relative to the «bright» types.

Thus, «demonstrative» elements may be present in the scan in much smaller quantities than «true» ones, however, attract the attention of both the expert and the neural network, which may eventually lead to an erroneous definition of the class. In order to separate these structures and analyze their role in determining the ISA, it is possible to use models for detecting characteristic objects [16-17]. Similarly, the scans have areas that do not contain characteristic elements. Such areas could be considered a «background» and separated in order to increase the contrast of «significant» areas by improving filtering [18]. The authors suggest that studying the role of «demonstrative» structures in the formation of the ISA will expand the recommendations for the subject and further individualize career guidance diagnostics.

As for the map of types and subtypes (Figure 18), it is being developed as a three-dimensional model for displaying the unique location of each subject. During the expansion of the sample, it turns out that there are also subtypes (E1) and transitional types (C and another hypothetical G) between the already existing ISA types according to the «Associative Color Space» © testing methodology, which have their own characteristics and recommendations.

Expanding the field of tasks will make testing as individualized as possible and will also allow you to evaluate the role of structures and objects that were not previously considered important or «characteristic», however, they can also serve as a source of additional information, which will improve the testing methodology and the image classification process.

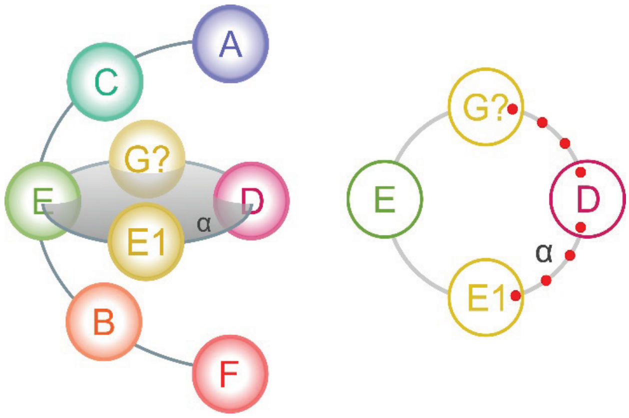

Figure 18: The layout of the map of types and subtypes, where the red dots are the possible positions of the scans of the subjects

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