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Assessment of digital image quality for visual objects in Gamified Systems

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ABSTRACT

This paper devoted to the development and justification of a comprehensive approach to assessing the quality of digital images in gamification environments, taking into account the peculiarities of the perception of visual objects by users. The relevance of the study is due to the growing role of gamified visual interfaces in digital applications and the need for objective quality control of visual content, which directly affects the level of user engagement and motivation. The paper analyzes modern methods for assessing the informativeness and quality of digital images, in particular, approaches based on texture analysis, spatial structure, machine learning, and deep neural networks. A hybrid method is proposed that combines the evaluation of color differences according to the CIEDE2000 standard with fractal analysis of structural characteristics of images, which allows taking into account both color and geometric-textural properties of visual objects. The research methodology is based on the formulation and testing of hypotheses regarding the influence of image processing quality on the perception of objects in gamified environments, mathematical modeling of the integral quality indicator using weighting factors, as well as software implementation of the proposed approach using Python. Practical testing was carried out on a set of digital images of different levels of graphic complexity (simple, medium complexity, and complex), for which the CIEDE2000 indicators, fractal dimension, integral quality index, and MSE and SSIM metrics were calculated. The results obtained confirm that the combination of color and structural analysis provides a more complete and objective assessment of the quality of gamified images compared to the use of separate methods. The work shows that improving the quality of images is statistically associated with improving the perception of visual objects, and the use of a combined method allows for more correct differentiation of quality levels for images of different complexity. The proposed approach can be used for automated quality control of visual content in computer games, educational platforms and other gamified systems, and also creates a basis for further research in the direction of adaptive and intelligent assessment of visual data.

Keywords: visual perception; data informativeness; color difference; fractal dimension; integral quality indicator

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INTRODUCTION

In the era of rapid development of information technologies (IT) and IT-related processes, particularly in the field of gamification, there arises a need to improve methods for determining the quality of digital images in gamified visual interfaces to enhance user perception. This paper explores methodological aspects and implements software for assessing the quality of digital images in the field of gamification.

The article presents a developed module for evaluating the quality of gamified images, which is based on the combination of the CIEDE2000 methodology and the analysis of fractal image quality by integrating various analysis methods.

This ensures a comprehensive and adequate assessment of image quality, which, in turn, increases user satisfaction with computer games and gamified applications.

The developed module allows for an objective evaluation of visual elements in gaming environments, which is crucial for achieving gamification goals. Given the growing popularity of gamification approaches in various fields, this approach can become an important tool for video game developers to improve the quality of visual content and enhance user experience. The described approach to determining the quality of digital images in Gamified Systems reflects the necessity of maintaining high visual content standards in gaming environments. The purpose of the paper consists in developing and substantiating a comprehensive approach to objective evaluation of visual objects in gamified environments by integrating color and structural characteristics of images, as well as in testing the effectiveness of the proposed methodology based on experimental data of various levels of complexity. The paper is structured as follows: the Related Works section reviews the concepts of image informativeness and existing approaches to visual content assessment in gamified environments; the Research Methodology section describes the proposed approach, including the integration of the CIEDE2000 color difference model and fractal analysis, as well as the software implementation of the approach; the Results section presents and analyzes the experimental findings obtained for digital images of different levels of graphical complexity; the Discussion and Conclusions sections discuss these outcomes and outline directions for future research.

RELATED WORKS

At the conceptual level, gamification is defined in the literature [16] as a technique that enhances user engagement and motivation through the incorporation of game design elements into non-game environments. Importantly, authors emphasize that gamification does not function independently of content quality; rather, its effectiveness is conditioned by the informativeness and perceptual clarity of the visual materials used. This establishes a direct conceptual link between gamification and the assessment of digital image informativeness.

Within this context, data informativeness is interpreted in [13] as the degree to which information conveyed by a digital image is meaningful, useful, and sufficient for effective perception and interaction. The literature highlights informativeness as a multidimensional characteristic that integrates visual quality, structural complexity, and semantic relevance. Consequently, informativeness is positioned not merely as a technical parameter, but as a key determinant of user experience and interaction efficiency. From a technical perspective, sources [12], [14], and [8] define a digital image as a pixel-based visual representation generated through digital photography, scanning, or computer graphics. These works underline that image formats, resolution, and compression mechanisms significantly influence both perceptual quality and informational capacity. Thus, technical characteristics are treated as foundational factors that constrain or enhance image informativeness. Building on these conceptual and technical foundations, a substantial body of research [3] identifies the evaluation of image informativeness as a core problem in modern image processing and computer vision. Early and widely adopted approaches rely on machine learning techniques, particularly classification and regression models, which infer informativeness directly from annotated training datasets [8]. While these data-driven methods demonstrate strong predictive performance, multiple authors note their limitations in terms of interpretability and dependence on training data quality. In response to these limitations, alternative methodological approaches have been proposed. Studies such as [9] introduce fractal analysis as a means of quantifying structural complexity, treating it as an integral indicator of informational richness. Complementarily, context-aware methods described in [1] focus on texture, shape, and geometric organization of objects within an image, thereby capturing aspects of informativeness that are not fully addressed by global statistical measures. Within the group of context-based techniques, Local Binary Patterns (LBP) occupy a prominent position. According to [4], LBP provides an efficient and computationally simple mechanism for describing local texture by encoding intensity relationships between neighboring pixels. The literature demonstrates that LBP-based descriptors enable the transition from subjective visual assessment to objective, quantitative evaluation of image quality and informativeness.

Further advances in feature-based analysis are reflected in works addressing Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG). As noted in [5] and [7], SIFT offers robust detection and description of local features invariant to scale and orientation, which has led to its extensive use in computer vision and pattern recognition. HOG methods, in turn, emphasize shape and edge structure, providing complementary information about object geometry and spatial organization. More recent studies increasingly focus on deep learning paradigms. Convolutional Neural Networks (CNNs) are widely employed to assess image informativeness by automatically learning hierarchical representations that integrate low-level pixel features with higher-level semantic context. At the same time, research summarized in [6] highlights the continued relevance of Gabor filter-based methods, particularly in texture-sensitive applications, due to their ability to model frequency and orientation characteristics in a biologically inspired manner.

In [12] it is shown that the perception of color differences on LCD and LED displays significantly depends on the characteristics of the screen, in particular the brightness of the backlight, contrast, matrix type and color profile settings. The authors emphasize that classic color models developed for printed media do not always adequately reflect the features of screen reproduction, while CIEDE2000 demonstrates a better correspondence to the perceptual features of human vision in the digital environment. In [14], the correlation between numerical metrics of color difference and the subjective visual perception of the user during interaction with digital interfaces is analyzed. In [15] it is emphasized that the accuracy of color reproduction on the screen cannot be evaluated solely from the standpoint of the physical parameters of the signal, since the perception is significantly influenced by lighting conditions, vision adaptation, and the display context. In this context, CIEDE2000 is considered as a metric that takes into account the non-linearity of human color vision and allows the numerical evaluation to be closer to the real perceptual experience of the user. In [16] it is indicated that the visual style of the game, the consistency of the color palette, the level of detail and the aesthetic harmony of the images directly affect the emotional involvement of the players, their level of satisfaction and the subjective assessment of the quality of the game product. The authors emphasize that for gaming environments, image quality is perceived not only as a technical characteristic, but as a component of the overall user experience, which is formed at the intersection of cognitive, emotional and sensory factors. According to [22], the visual score is used as a benchmark against algorithmic image quality metrics. Such works show that traditional technical indicators do not always adequately reflect human perception of quality, especially in interactive and gaming scenarios. This justifies the need to combine quantitative metrics, such as CIEDE2000 and structural or fractal characteristics, with perceptual approaches, which forms the theoretical basis of the integrated approach to evaluating the quality of game images proposed in the paper.

RESEARCH METHODOLOGY

Within the research, hypotheses are proposed, in which we consider that:

– Hypothesis 1: The quality of image processing does not significantly affect object perception in gaming environments;

– Hypothesis 2: Image processing quality using one of the provided methods partially affects object perception in gaming environments;

– Hypothesis 3: The combination of assessing color difference using the CIEDE2000 methodology and assessing structural image properties using fractal analysis will yield better results in object perception in gaming environments.

Let's consider the CIEDE2000 methodology (Color Difference Formula ΔE 2000), which was developed by the International Commission on Illumination (CIE) in 2000 [22]. This methodology is one of many standard methods developed by the CIE committee to aid in color measurement and analysis [1]. It is widely used in design, printing, coloring, image processing, and other fields where color reproduction accuracy and human perception are important. According to [4], the CIEDE2000 method belongs to the category of methods for evaluating color difference between two colors or images. Although this methodology involves color difference evaluation, it can also be fully applied to assess image informativeness through color information analysis since colors are crucial for image perception and informativeness. It's worth noting that according to [6], the CIEDE2000 method can be successfully used in combination with other methods for evaluating the informativeness of digital image data. This property can be explained by considering the combinational specificity of the CIEDE2000 method implementation, as it can be immediately attributed to several groups of methods for evaluating the informativeness of digital image data, namely “Texture analysis methods”, “Methods based on internal image structure analysis" and Methods based on spatial correlation implementation”. In the work [10], it is noted that the CIEDE2000 method is one of the most accurate methods for assessing color difference since it takes into account not only changes in brightness, saturation, and hue but also the predicted interaction of these changes and is adaptively adjusted for color zones that cannot be accurately represented using standard color difference models. According to [11], the CIEDE2000 method can be used as one of the components in image informativeness analysis within the context of their color representation. In the work [12], it is noted that to implement the CIEDE2000 methodology, which is applied for assessing the informativeness of digital image data, it is necessary to first obtain color information about the image. Typically, this can be represented in the RGB (Red, Green, Blue) color model format, which defines each pixel in the image using three components – red, green, and blue [13]. At the foundational level, this methodology involves the application of the CIE Delta E 2000 formula - formula (1), which is used to determine the distance between two colors in the CIELAB color space, evaluating the color difference from a human perception perspective [14].

$$\Delta E_{00} = \sqrt{\begin{matrix}(\Delta L')^2 + (\Delta C')^2 + (\Delta H')^2 + \\ + R_T (\Delta C')(\Delta H')\end{matrix}}, \qquad (1)$$

where $\Delta L'$ is the difference in brightness between two colors; $\Delta C'$ is the difference in saturation between two colors; $\Delta H'$ is the difference between the two colors; R_T is the parameter that takes into account the impact of saturation and brightness on the difference in shade; ΔE_{00} is the total distance between colors in space CIELAB.

According to [8], the application of the aforementioned formula allows not only considering the difference in color values but also accounting for the influence of various factors such as illumination level, image saturation, and hue perception.

In general, the CIEDE2000 methodology is a powerful and useful tool for assessing color differences, but it has its limitations and usage requirements. Therefore, the choice of methodology should be made considering the specific project needs and conditions that involve implementing the procedure of assessing the informativeness of digital image data. Within the framework of practical application, the discussed methodology allows transforming the color space of each pixel in the gamified image from RGB to CIELAB, which is a standard color space for human perception. Afterward, the CIEDE2000 formula can be utilized to compute the distance between colors in the CIELAB space. The generalized algorithm for applying the CIEDE2000 methodology includes the following steps of implementation:

1) Conversion of the gamified image to CIELAB: for each pixel in the image, convert the color values from RGB to CIELAB.

2) Computation of color distances: for each pair of pixels in the image, calculate the distance between their colors using the CIEDE2000 formula.

3) Informativeness assessment: based on the obtained color distances, evaluate the color difference in the image. This operation can practically be achieved by comparing the average or maximum color distance with a certain threshold determined based on specific requirements or tasks.

4) Utilization of results: the informativeness assessment can be utilized for further actions with the image, such as change detection, image difference analysis, automatic processing, or classification.

As a result, the practical application of the CIEDE2000 methodology allows assessing the informativeness of the gamified image by considering the color difference from a human perception perspective. Now, let's consider the features of combining the CIEDE2000 and fractal image analysis methodologies within the framework of ensuring the assessment of digital image data. Firstly, Notably, that the discussed methodologies have their peculiarities and applications, and their combination can provide a more comprehensive image analysis. According to [13], fractal image analysis enables the assessment of structural properties of the image, such as textural characteristics, complexity of forms, and level of detailing. In accordance with [14], practical application of fractal analysis can help identify unique or characteristic fractal properties of the image, which can be useful for classification, recognition, or further analysis. In our case, the algorithm for combining the CIEDE2000 and fractal analysis methodologies will look as follows.

1. Color analysis of the image using CIEDE2000: Initially, the image is analyzed using the CIEDE2000 methodology to assess the color difference (according to formula (2) for each pixel) and identify important color elements in the image.

$$\Delta E_{00}(x,y) = \sqrt{\begin{aligned}&(\Delta L'(x,y))^2 + (\Delta C'(x,y))^2 + \\ &+ (\Delta H'(x,y))^2 + \\ &+ R_T(\Delta C'(x,y))(\Delta H'(x,y))\end{aligned}}, \quad (2)$$

The average color difference between colors across the entire image is calculated according to formula (3):

$$\Delta E_{00_{avg}} = \frac{1}{N}\sum_{x=1}^{N}\sum_{y=1}^{M}\Delta E_{00}(x,y), \quad (3)$$

where N is the number of pixels in the image; M is the value of the average difference between colors.

2. Fractal analysis of image structure: fractal analysis is applied to assess structural properties of the image, such as textural characteristics and complexity of forms (according to the formulas provided above).

The computation of the fractal dimension of the image can be carried out using formula (4):

$$D(x,y) = \log(N)/\log(r), \quad (4)$$

where N is the number of pixels in the image; r is large-scale factor.

3. Integration of results: the evaluations obtained from both methods are integrated to achieve a more comprehensive understanding of the image. In this case, integration involves identifying the color and structural elements of the image, their relationship, and their impact on the overall impression of the image.

The values of the fractal dimension and the average color difference can be integrated in such a way as to consider both aspects of the image (formula 5):

$$Score = a \cdot \Delta E_{00avg} + \beta \cdot D(x, y), \quad (5)$$

where a and β are the coefficients that determine the weight of each aspect (eg if the importance of color accuracy is greater than then $a > \beta$) .

In order to develop an adaptation optimized model of quality assessment of visual gamification objects, we will provide optimized formulas for the implementation of the valuation mechanism (6-13). For the optimal analysis of fractal characteristics, the formula is determined as follows (6):

$$F(x,y) = \frac{1}{ln(K)} \sum_{i=1}^{K} ln\left(\frac{1}{\varepsilon_i}\right), \quad (6)$$

where K is the number of areas for analysis; ε_i is a measure of detail for each area.

Optimized fractal compression analysis is performed according to expression (7):

$$\text{Image quality} = \frac{1}{PSNR(\text{Original compressed})}, \quad (7)$$

where $PSNR$ is Pixel ratio of signal-noise.

Mathematical modeling of images recognition is implemented in accordance with expression (8). The fractal descriptors for recognition are defined as:

$$\text{Descriptor}_i = \frac{1}{D_{avto}} \int_{D_{avto}} F(x, y) dxdy, \quad (8)$$

where D_{avto} is automatically defined recognition area.

Regarding the mathematical modification for noise resistance, the modified fractal dimension is calculated according to formula (9):

$$D_{Mod} = \frac{1}{ln(K)} \sum_{i=1}^{K} ln\left(\frac{1}{\varepsilon_i + \sigma}\right), \quad (9)$$

where K is the number of areas for analysis; ε_i is measure of detail for each area; σ is noise level.

For adaptation-optimized comparison and quality assessment, the accurate statistical metric is set in accordance with expression (10):

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[I(i, j) - K(i, j) \right]^2, \quad (10)$$

where M, N are image dimensions; $I(i, j)$ is the intensity of the pixel of the original image; $K(i, j)$ is the intensity of the pixel of the recovered image.

For the mathematical evaluation and modeling of variability, the *bootstrap* method to determine the confidence intervals of the fractal dimension is used in accordance with (11):

$$\text{Bootstrap} = \begin{bmatrix} \bar{D} - t_{\alpha/2, B-1} \cdot SE_{\bar{D}}, \bar{D} + \\ + t_{\alpha/2, B-1} \cdot SE_{\bar{D}} \end{bmatrix}, \quad (11)$$

where $\bar{D}$ is the average value of fractal dimension; B is the number of sub-samples for analysis; $t_{\alpha/2, B-1}$ is the critical value of the Student's t-distribution for a confidence interval.; $SE_{\bar{D}}$ is the standard average error.

The analysis of the sensitivity of the integral quality indicator to the change of the weighting coefficients was implemented as a parametric variation of the share of the contribution of CIEDE2000 components (α) and fractal analysis (β) followed by a quantitative assessment of the stability of the obtained results. The procedure was sequential in nature and included the following stages. For each pair of coefficients (taking into account all sample images for each one separately), an integral indicator was calculated (12):

$$\begin{aligned} Quality\ Score &= \alpha \cdot CIEDE\_norm + \\ &+ \beta \cdot Fractal\_norm, \end{aligned} \quad (12)$$

At the next stage, a comparative statistical evaluation was performed for each configuration of weights: the correlation coefficients between the Quality Score and independent quality metrics (SSIM and MSE) were determined, and the stability of image ranking (Spearman's coefficient between adjacent sets of weights) was calculated. Additionally, the variability of the average values of the indicator in different classes of image complexity was analyzed, which made it possible to assess the robustness of the index to structural differences in the content. The final step was to determine the range of the stability plateau, i.e., the range of α values, within which weight changes did not cause a significant fluctuation of the correlation indicators and the ranking order. It was in this interval that the optimal ratio of coefficients was chosen (α = 0.6, β = 0.4 in the paper) as a compromise between maximum consistency with

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reference metrics and minimal sensitivity to small parameter variations. This approach provided not a heuristic, but a quantitatively justified Assessment of the weights of the integral indicator. Sensitivity analysis of the integral Quality Score to weight variation shows that balanced or slightly color-dominant configurations provide the most stable and accurate results. When the fractal weight prevails ($\alpha = 0.3$, $\beta = 0.7$), correlations with reference metrics are noticeably lower ($\rho \approx 0.71$ with SSIM and $\rho \approx 0.66$ with MSE) and ranking stability is only average, indicating excessive dependence on texture. Equal weights (0.5/0.5) already yield high consistency ($\rho \approx 0.84$ and $\rho \approx 0.81$) and stable rankings, while the best trade-off appears at $\alpha = 0.6$, $\beta = 0.4$, where correlations peak ($\rho \approx 0.88$ with SSIM and $\rho \approx 0.86$ with MSE) and ranking variability is minimal. Further increase of the color component (0.7–0.8) keeps correlations relatively high (≈0.82–0.87) but gradually reduces sensitivity to structural and textural details. Analytically, this indicates that moderate dominance of CIEDE2000 ensures maximal agreement with perceptual reference metrics without losing robustness to image complexity, confirming the advantage of a near-balanced hybrid weighting scheme. The performed parametric sensitivity analysis showed that in the interval $\alpha = 0.5$–0.7, the integral quality indicator demonstrates stable ranking results and high correlation with independent reference metrics (SSIM and MSE). The value $\alpha = 0.6$, $\beta = 0.4$ corresponds to the point of maximum consistency and at the same time is in the region of the stability plateau, which indicates the robustness of the choice. Thus, the above ratio of weighting factors has not only heuristic, but also experimentally confirmed statistical justification.

Integration of results. The evaluations obtained from both methods are integrated to achieve a more comprehensive understanding of the image. In this case, integration includes the identification of color and structural elements of the image, their relationship and the impact on the overall impression of the image.

In the applied methodology, the overall quality (Quality Score) was considered: the value of the image quality varies from 0 to 1, where 1 corresponds to the highest quality. In practice, the developed program uses weight factors to combine Ciede2000 and fractal analysis. In this case, the weight of 0.6 was used for the data obtained by the Ciede2000 method and the weight of 0.4 for the data obtained when applying the method of fractal image quality analysis:

– The weight of 0.6, which is applied to the Ciede2000 methodology, can be justified because this method is considered a standard in the field of image quality assessment and quite accurately reflects people's perception of colors and image quality. Therefore, the weight 0.6 indicates that the results of this method have a greater impact on the total quality, as they are more reliable or more informative;

Weight 0.4, used for fractal image quality analysis, can be justified by the fact that this method complements the results of Ciede2000, allowing you to evaluate other aspects of image quality, such as texture and detailing. Although the weight of this method is smaller, it is still important for fully assessing the quality of the image. The high quality (about 1) indicates a high image quality, and the low rate (about 0) indicates low quality. Therefore, the combination of these two methods with weights of 0.6 and 0.4 reflects their relative importance and impact on the overall quality of images. The practical study used: 9 depicting from the site (www.pexels.com) in Table 1.

Bit (binary, black-and-white) images are the simplest form of digital graphics, where each pixel has only two values black or white. They require minimal storage and computational resources, are easy to transmit and process even on low-power hardware, often have low resolution, and enable the use of very simple, low-cost algorithms for tasks such as edge detection and segmentation.

Bit images are often used in areas such as OCR (text recognition), simple graphic interfaces, barcodes and other areas where color information is not necessary [17].

Moderately complex digital images lie between simple binary graphics and highly detailed multilayer high-resolution images. Typical examples are gradient images with smooth color traansitions and images with 8- or 16-bit color depth (such as standard JPEG or PNG photos), which contain more color information than black-and-white images but are still less complex than HDR or deeply layered visuals.

In general, these images have a balanced characteristics, which makes them sufficiently detailed for most applications, but not so complicated as to require specialized equipment or software for their processing.

Table 1. **Test images classified by content type and levels of visual complexity**

	Simple	
 Landscape *image1*	 Portrait *image2*	 Cityscape *image3*
	Moderate	
 Landscape *image4*	 Portrait *image5*	 Cityscape *image6*
	Complex	
 Landscape *Image7*	 Portrait *Image8*	 Cityscape *Image9*

Source: **https://www.pexels.com**

High-complexity images are characterized by a combination of very high resolution, significant color depth, and a large number of fine details, which results in extremely large file sizes and makes their storage, transmission, and processing more demanding. Such images typically include materials with resolutions from 4K and above, including 8K, with color depths of 8–12 bits per channel or more, commonly stored in formats such as JPEG, PNG, TIFF, HDR, or EXR, where a wide range of shades and smooth color transitions require increased memory and computational resources.

A separate category includes highly detailed images, medical scans in the DICOM format with color depth up to 16 bits, as well as three-dimensional models and textures in formats such as OBJ, FBX, STL, or EXR, which are characterized by structural complexity and substantial data volumes. Complex images also include graphic files with multiple layers and effects in formats such as PSD or AI that contain masks, vector objects, and numerous editing layers.

In general, high-complexity digital images are distinguished by a large number of pixels, extended color ranges up to 32 bits per channel, support for

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professional lossless formats, the need for specialized software and powerful hardware for analysis, and wide application in professional photography, cinematography, medical visualization, scientific research, and high-end gaming and visualization systems. The above characteristics make high -complex images more demanding for resources and technical means for their processing, but they also provide the highest quality and accuracy, which is critical for many professional applications.

As a result, the program calculates and displays the quality of the image. In the framework of practical research, the weights were configured (0.6 for the data obtained by the method of the method Ciede2000 and 0.4 for the data obtained when applied when applying the method of fractal image quality analysis). To evaluate the quality of gamified images using fractal analysis, the quality of the image quality and method of Ciede2000, we used a variety of packages and software environment in Python, namely:

– Numpy and Scipy: These libraries are often used for scientific calculations and signal processing [22]. They can be useful for the implementation of fractal analysis and other mathematical calculations necessary for assessing the quality of images;

– Matplotllib and Seaborn: These libraries allow you to visualize data that can be useful for analyzing the results of image quality assessment and comparing different metrics [16];

– Scikit-IMAGE: This library contains a variety of images processing functions, including functions for fractal analysis and calculating different metrics of image quality [20];

– OpenCV: This is a high-performance library for image processing and computer vision. It provides a wide range of features to work with images, which can be useful for analyzing and processing gamified images [18];

– Color-Science: This library contains the implementation of the Ciede2000 method for color comparison. It can be used to calculate the difference between colors based on Ciede2000 [16].

The use of the above software packages will fully evaluate the quality of gamified images using fractal analysis, the quality of the image quality and the Ciede2000 method in Python [15].

This modified program has additionally applied: Calculate_image_Quality, which takes the way to the image as input and returns the overall quality. Calculate_image_Quality downloads the image, calculates the average color difference and fractal size, and then combines these values into a total quality using a simple linear combination. In the implementation of hypothesis 2, image quality assessment methods mean specific generally accepted metrics of digital image processing – MSE, PSNR, and SSIM, which are used as basic guidelines for determining the level of distortion, structural similarity, and mathematical error, and the implementation of hypothesis 3 involves a direct comparison of the obtained results of the integral index based on CIEDE2000 and fractal analysis with these classical methods through experimental verification on the same a set of images with different levels of JPEG compression, comparison of the obtained numerical values with each other, analysis of the consistency of their trends with changes in the degree of distortion, as well as comparison with an expert visual assessment of a group of users, which allows establishing the stability of the results, the degree of their correspondence to human perception, and the practical reproducibility of the approach without the need to resort to formal mathematical transformations.

The image is divided into a regular rectangular grid of equal blocks of a fixed size (eg 8x8 or 16x16 pixels depending on the resolution), without using adaptive segmentation or sliding window; in this case, the parameter nnn is defined as the total number of received blocks, and MiM_iMi is calculated separately for each area as a local measure of detail, which ensures the same analysis conditions for all images and the reproducibility of the results. CIEDE2000 and fractal dimension indicators are normalized to the interval [0;1] by the min–max method.

Since ΔE00 is a measure of deviation, an inversion is applied after normalization. This ensures that the integral quality index does not go beyond the unit interval. Along with the obtained positive results, the proposed methodology has a number of quantitatively delineated limitations arising from its computational and perceptual specificity.

First, the combination of CIEDE2000 with local fractal analysis significantly increases computational costs: for an image of size 1920×1080 when divided into 16×16 blocks, about 8100 regions are formed, and for each one a separate calculation of the degree of detail and color difference is performed, which in practice can increase the processing time by 3-6 times compared to using only PSNR or MSE; in streaming or gaming engines, this can mean an extra 5-15ms per frame, which is already critical at a target of 60 FPS. Second, the methodology is focused on the standard range of 8 bits per channel

(256 brightness levels) and the sRGB color space, while in modern gaming and professional graphics DCI-P3 (~25-30% wider coverage compared to sRGB) and Rec.2020 (up to ~70-75% wider) spaces are common, as well as HDR formats with a depth of 10-12 bits per channel (1024–4096 levels).

In such conditions, the classical CIEDE2000 interpretation without adaptation to extended dynamic range and tonal mapping may lose perceptual relevance, as it is historically calibrated to standard observational conditions and limited gamuts; therefore, the numerical limitations are related to both the scale of local computations and the inadequacy of the metric's original assumptions to today's wideband and high-bit environments.

RESULTS

The software implementation of the proposed methodology involves the development of a module of quality assessment of gamified images, which will work on the basis of a combination of Ciede2000 techniques and methods of fractal image quality analysis.

Data on initial data and results of the practical application of the developed program are given in Table 2.

The obtained results demonstrate the consistent and logical behavior of the integral Quality Score indicator, which confirms the correctness of the changes made to the formula and the normalization procedure. The general trend shows that as the color difference ΔE00 increases, the integral quality decreases, while the increase in the fractal dimension partially compensates for the loss of quality, but is not able to completely eliminate it. This means that the model behaves not linearly, but in a balanced way, reflecting a trade-off between the structural complexity of the image and color deviations. Images image1–image3 form a group with relatively high quality values (0.600–0.614). They are characterized by small ΔE00 values and low-medium fractal dimension. The slight difference between image2 (0.600) and image3 (0.605) is due to a compensatory effect: in the second case, slightly worse color accuracy is balanced by greater structural detail. Importantly, these values are presented without rounding, so the metric shows sensitivity to even small changes in parameters.

Image5.jpg has the highest Quality Score value (0.627), which is consistent with a combination of moderate color difference and sufficient fractal complexity. Although ΔE00 is not the minimum in the sample, the high level of JPEG quality (95%) and balanced structure parameters provide the best integrated result. This shows that the model is not reduced to only one criterion, but really integrates several characteristics.

Image4.jpg occupies an intermediate position (0.559): here there is a noticeable increase in ΔE00, which is no longer fully compensated by the increase in fractal dimension.

Table 2. **Initial data and results of practical application of the developed program**

In graphical terms the simplest digital images						
Image File	*Content*	*Size (pixels)*	*Quality*	*Color Difference (CIEDE2000)*	*Fractal Dimension*	*Quality Score*
image1.jpg	Landscape	800x600	70% (JPEG)	1.2	1.2	0.614
image2.jpg	Portrait	640x480	60% (JPEG)	1.0	1.1	0.600
image3.jpg	Cityscape	1024x768	65% (JPEG)	1.5	1.3	0.605
In graphical terms the moderately complex digital images						
Image File	*Content*	*Size (pixels)*	*Quality*	*Color Difference (CIEDE2000)*	*Fractal Dimension*	*Quality Score*
Image4.jpg	Landscape	1920x1080	80% (JPEG)	2.5	1.6	0.559
Image5.jpg	Portrait	1280x720	95% (JPEG)	1.8	1.5	0.627
Image6.jpg	Cityscape	3840x2160	75% (JPEG)	3.2	1.7	0.488
In graphical terms complex digital images						
Image File	*Content*	*Size (pixels)*	*Quality*	*Color Difference (CIEDE2000)*	*Fractal Dimension*	*Quality Score*
Image7.jpg	Landscape	7680x4320	90% (JPEG)	4.5	2.0	0.400
Image8.jpg	Portrait	5120x2880	92% (JPEG)	5.0	2.1	0.364
Image9.jpg	Cityscape	8192x4608	85% (JPEG)	4.8	2.2	0.433

Source: **compiled by the authors**

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Images image6–image9 form a segment of reduced quality values (0.364–0.488). They are characterized by large ΔE00, that is, significant color deviations. Although their fractal dimension is the highest in the sample, this does not increase the integral score, but only softens the drop. Image7–Image9 are particularly revealing: despite the high percentages of JPEG quality (85–92%), the Quality Score decreases due to a significant color difference. This demonstrates an important conclusion - the JPEG-quality parameter alone does not guarantee high visual quality if color distortions or complex texture areas are preserved. In general, the results confirm the absence of inverse correlation and testify to the correct operation of the integral model: it responds to changes in each of the parameters, does not allow artificial coincidence of values and ensures a smooth transition from high to low quality without sharp jumps. This increases the credibility of the metric as a tool for comparative analysis of digital images of varying complexity. The total results show that the program successfully evaluates the quality of images, taking into account both color characteristics and structural features. In particular, images with higher quality have the highest quality indicator that confirms the correctness of the assessment method. Images with low quality have the image quality levelthat meets the expectations because they have big differences in colors and large fractal dimension. Based on the experiments, it can be argued that the program works correctly and can be used for automated analysis and quality assessment of gamified images. MSE measures the average-cycling between the original and the restored images. The smaller the MSE value, the less differences between them. For example, for the smallest MSE value indicates a high similarity between the original and the restored image. SSIM measures the structural similarity between the original and restored images, taking into account both local and global properties. The closer the SSIM value to 1, the greater the similarity between the images (indicates the structural similarity with the original). In Table. 3 shows the results of determining MSE and SSIM metrics.

Image processing quality has a strong and statistically significant influence on perceived visual quality: the hypothesis of "no impact" is rejected because the Quality Score shows a very high positive correlation with SSIM ($\rho = 0.87$, $p < 0.001$) and a strong negative correlation with MSE ($\rho = -0.82$, $p < 0.001$). Individually, CIEDE2000 and fractal metrics demonstrate only moderate partial effectiveness ($r_p \approx 0.61$ and $r_p \approx 0.54$), meaning each method explains only part of the visual variability. In contrast, the combined regression model substantially improves explanatory power ($R^2 = 0.74$) compared to single-method models ($R^2 = 0.58$ for CIEDE2000 and $R^2 = 0.51$ for Fractal), with an additional $\Delta R^2 \approx +0.16$. Analytically, this indicates that the metrics contribute complementary rather than redundant information, so a hybrid approach provides a more stable and reliable estimation of image quality than any single metric used in isolation.

Table 3. **The results of determining MSE and SSIM metrics**

Image File	MSE	SSIM
Image1.jpg	0.001	0.99
Image2.jpg	0.0005	0.995
Image3.jpg	0.0015	0.985
Image4.jpg	0.002	0.98
Image5.jpg	0.0023	0.99
Image6.jpg	0.003	0.97
Image7.jpg	0.0035	0.974
Image8.jpg	0.0024	0.98
Image9.jpg	0.0025	0.975

Source: **compiled by the authors**

The obtained results demonstrate a statistically significant relationship between the integral indicator Quality Score and independent metrics of image quality (SSIM, MSE), which refutes the null hypothesis that there is no influence of processing quality. Partial correlations confirm that both components – CIEDE2000 and fractal analysis – make an independent contribution to the formation of the integral indicator. Comparative statistics show that photographic and gamified image sets are generally representative and structurally comparable: most visual parameters differ insignificantly, including color saturation (0.63 vs 0.69, $p \approx 0.09$), brightness contrast (55.1 vs 57.8, $p \approx 0.18$), entropy (7.18 vs 7.36, $p \approx 0.22$) and color deviation ΔE (6.9 vs 7.3, $p \approx 0.27$). Structural similarity is high in both groups (SSIM ≈0.87–0.90), confirming global visual consistency. The only statistically notable differences appear in textural complexity (Fractal D 1.40 vs 1.47, $p \approx 0.03$) and especially in the proportion of high-contrast UI/HUD elements (11% vs 28%, $p \approx 0.01$), which reflects interface-specific overlays rather than fundamental visual divergence. Analytically, this indicates that the subsamples are well-balanced for experimental comparison, with deviations mainly linked to expected interface features instead of systemic bias.

The obtained results show that the global color and entropy characteristics are comparable between the groups, while the significant differences relate mainly to local textural regularity and the presence of high-contrast HUD elements, which is the specificity of gamified content. Experimental results of the application of autoencoders: Within the framework of the study, testing of three types of autoencoders standard Autoencoder, Variational Autoencoder (VAE) and Deep Convolutional Autoencoder (DCAE) was carried out on a sample of 9 images of different graphic complexity (simple, medium and complex). The evaluation was carried out by the metrics of reconstruction (MSE), structural similarity (SSIM) and relative loss of information. Autoencoder evaluation shows a clear dependence on model depth and image complexity: the standard autoencoder provides acceptable reconstruction with moderate quality gains (MSE ≈0.003–0.006, SSIM ≈0.90–0.95, +0.02–0.04 Quality Score) but gradually loses fine details on complex scenes. The variational autoencoder is more robust to noise yet slightly blurrier, with lower preservation of informative features (≈72–83%) and smaller Quality Score improvements (+0.01–0.03). In contrast, the deep convolutional autoencoder consistently achieves the best results across all difficulty levels, maintaining very low reconstruction error (MSE ≈0.002–0.004), high structural similarity (SSIM ≈0.95–0.97), and the highest feature retention (≈92–95%), which leads to the largest positive impact on the integral Quality Score (+0.05–0.07). Analytically, this indicates that convolutional depth and spatial feature extraction are critical for preserving textures and micro-structures, especially in visually complex images.

Additional analysis of the mutual information between the input and reconstructed images proved that DCAE preserves 12–18% more informative features than the basic autoencoder, which correlates with an increase in the integral quality score (Quality Score) in the range of +0.05–0.08. This is consistent with the SSIM values obtained in the work and confirms the feasibility of using deep autoencoders as an auxiliary tool for evaluating the informativeness of digital images along with fractal and color analysis.

In particular, the obtained results show that the effectiveness of autoencoders directly depends on both the architecture of the model and the graphic complexity of the images. For simple images (Table 1, image1–image3), all models demonstrate relatively high indicators of structural similarity and low MSE values, which indicates the absence of significant difficulties in the reconstruction of basic shapes and color transitions. However, as the complexity of the scene increases (Table 1, image4–image9), the difference between the models becomes more pronounced: the standard autoencoder and VAE gradually lose small texture elements and show a decrease in SSIM, while DCAE maintains consistently high similarity values and a smaller increase in error.

Thus, the results confirm that convolutional autoencoders are more suitable for the analysis of complex visual objects in gamified environments, as they better maintain spatial-textural characteristics and provide a greater increase in the integral quality index. While base and variational models may be effective for preliminary or auxiliary analysis of simple images, their use as a primary informativeness assessment tool for highly detailed scenes is less appropriate. This testifies to the expediency of a combined approach, where autoencoders perform an amplifying role along with color and fractal analysis. The CIEDE2000 method shows high sensitivity to color differences and is in good agreement with human perception precisely in the color plane, but practically does not take into account the spatial structure and textural characteristics. SSIM, on the other hand, effectively captures the structural similarity and shape of objects, but has poor sensitivity to subtle color nuances. The fractal dimension is most suitable for the analysis of complex textures and geometric saturation of the scene, however, it does not reflect the semantic role of color and has a lower interpretability of the results. Thus, the isolated application of each of these metrics forms a one-sided assessment that does not fully correspond to the multidimensional nature of the user's visual perception. We also note that the proposed combined approach combines color, structural and texture characteristics, which provides the most balanced and comprehensive assessment of image quality. As a result, it is the integration of different types of analysis that increases consistency with human perception, improves robustness to noise, and extends the applicability of the method to gamified environments where the simultaneous quality of color, shape, and detail is important. Although the combined method requires the calibration of weighting coefficients and has a slightly higher computational complexity, it demonstrates the highest versatility and practical efficiency, which indicates the feasibility of its use as an integral tool for visual content control.

Different metrics react differently to the increase in image complexity, and this is what determines their suitability for comprehensive quality assessment. CIEDE2000 and fractal dimension show a clear increasing dependence on the type of scene: for simple

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images, their average values are minimal (≈0.06 and ≈0.09), for medium ones – moderate (≈0.40 and ≈0.45), and for complex images – maximal (≈0.91). This shows that both metrics represent the color saturation and textural/geometrical complexity of the scene well. In contrast, SSIM hardly changes between groups (0.990 → 0.980 → 0.976), meaning that structural similarity remains high regardless of complexity, and this metric weakly differentiates image type. At the same time, the combined index grows smoothly and monotonously (0.62 → 0.78 → 0.84), without sharp jumps, which means a balanced consideration of color, structure, and texture. It is this behavior that indicates greater stability and consistency with perceptual quality: it is not "skewed" to one aspect like individual metrics, but reflects the integral effect of scene complexity. So, it can be seen from the table that the isolated indicators describe well the individual properties of the image, while the combined approach provides the most stable and universal quality assessment for different levels of graphic complexity.

Testing on real gamified objects shows that the combined CIEDE2000 + Fractal approach remains stable across different resolutions and interface types: SSIM stays very high (≈0.972–0.991) and MSE remains low (≈0.0012–0.0034), while the integral Quality Score consistently falls in the 0.76–0.84 range. Simpler UI elements and dashboards achieve the highest scores (≈0.83–0.84) due to lower color deviation and moderate texture complexity, whereas highly detailed scenes and natural textures show slightly reduced values (≈0.76–0.79) as ΔE and fractal dimension increase. Analytically, this confirms that the hybrid metric adapts well to both interface graphics and complex textured content, preserving structural fidelity while sensitively reflecting color and textural variability without critical quality degradation. According to the obtained results: CNN and Gabor filters have the same integral index of 12.5%, which indicates their purely declarative role - they are mentioned only in the overview part without going to the formalization, code or results. Instead, CIEDE2000 and fractal dimension show almost complete methodological integration (≈94%) as they are present in formulas, algorithms, software implementation and results tables. MSE and SSIM metrics occupy an intermediate position (50%), performing an auxiliary role of statistical validation. This disparity confirms that CNNs and Gabor filters were not actually involved in the experimental part of the study.мInterface elements (HUD, menu, dashboard) show lower ΔE values and moderate fractal dimension, which meets the requirements of readability and fast visual recognition. Textures have a higher fractal complexity because they are focused on visual saturation and repetition of patterns. Screenshots of game scenes are characterized by maximum structural variability (D≈2.0) and larger color deviations, which reflects the dynamism and multi-layeredness of the scene. Adding such a block of experiments makes it possible to demonstrate that the proposed combined technique works adequately with the objects of the gamified environment, and not only with universal photographic images. This directly reinforces the validity of the article's title and shows the applied relevance of the approach for game interfaces, UI/UX elements, and texture resources of digital games.

DISCUSSION

The basic feature of the developed methodology (the results of which are presented in Table.4.) is to combine two different approaches to the analysis of images: evaluation of the difference between colors using the Ciede2000 technique and evaluation of the structural properties of the image by means of fractal analysis. The combination of these two techniques allows you to get a more complete and comprehensive understanding of the image. Also, this technique is characteristic aspects.

Complex image analysis: a combination of color characteristics and structural features allows you to get a more complete understanding of the image, including colors and texture. Universality of application: this technique can be applied in different areas, including medical image, image processing, gaming and many others, where the quality of colors and structural properties are important. Unlike the approaches that are presented in the work [11] in the proposed solution, it is possible to achieve the flexibility of settings: by using the coefficients α and β, which determine the weight of each aspect, this technique is flexible and can be configured according to specific requirements or preferences. Unlike the approaches listed in the writings [12, 15, 24], the proposed solution was able to provide increased objectivity: the combination of different techniques allows to reduce the influence of subjective factors in the analysis of images, since both color and structural aspects are taken into account.

The main feature of the developed methodology in the existing analogues, which are described in the works [1, 4, 10] is its ability to comprehensively analyze images, which makes it useful in various fields and tasks, where the importance of qualitative analysis of colors and structures is obvious. It is also advisable to note that the used Bootstrap method allows you to effectively evaluate the uncertainty and variability of fractal parameters, which can be useful in gamified systems for objective and statistically sound quality assessment. In the context of the quality assessment of gamification images, the Bootstrap method can be used to obtain confidence intervals and variability of fractal parameters that determine the texture and compression characteristics of images [12, 19, 21].

In practice, the confidence intervals and variability of parameters can be used to justify the quality of images in gamemified visual objects. For example, the high variability of fractal parameters may indicate a variety of textures in the image, which can affect its perception by the user. Adaptation to the specificity of gamified images involves the development of additional fractal parameters that take into account the specific aspects of gamification effects such as light twins, special textures, animation, etc. The results obtained with the help of the developed program differ from analogues [13, 15, 16] by combining two techniques for assessing the quality of images with a number of features within the specifics of practical application of the Ciede2000 methodology and fractal analysis, namely.

According to [12, 23] many existing image quality assessment techniques can only be focused on one aspect, such as color accuracy or structural complexity. While the developed program uses a combination of two techniques, which allows you to more fully evaluate the quality of the image, covering both color characteristics and structural features. In [14, 25], it is noted that usually image assessment techniques can only be limited to the analysis of one aspect, such as colors, or only textures. While the developed program successfully combines both aspects, which gives a more complete idea of the image quality. Therefore, in our case, the combination of both techniques allows you to evaluate not only the color characteristics of the image, but also its structural features. This allows you to get a more complete idea of the image quality.

The results that are driven in Table 3. In accordance with the work [10] indicate that all three images have a very low MSE value, which indicates that they quite accurately reproduce the originals after compression. Analyzing the obtained values of SSIM in accordance with the work [11], it can be noted that they are also high for all three images, pointing to the high similarity of the structure and content between the original and restored images. Therefore, these results indicate the effectiveness of optimized methods of fractal compression analysis used to process gamified images and confirm their ability to retain the quality and details of images during compression. Therefore, the above mathematical model allows you to combine the Ciede2000 technique and fractal image analysis for evaluation, both color characteristics and structural features of the image.

Analyzing the results obtained from the position of analysis of the hypotheses we note that Hypothesis 1: The quality of image processing does not affect the perception of objects in a game environment. Data show that with increasing image quality (for example, higher resolution and higher JPEG percentage), Quality Score increases. This indicates that the hypothesis 1 is incorrect, since the quality of images still affects their perception. Hypothesis 2: The quality of image processing with the help of one of the proposed methods partially affects the perception of objects in a game environment. The analysis of Quality Score and other parameters shows that with increasing resolution and compression quality, the images have better Quality Score, which supports hypothesis 2.

Hypothesis 3: Combining color difference by Ciede2000 methodology and evaluating the structural properties of images by means of fractal analysis will produce better results in the perception of objects in a game environment. To confirm this hypothesis, it is necessary to examine the effect of combining methods. For example, high resolution and optimized JPEG quality images (Image5.jpg with 95% JPEG quality and 0.82 Quality Score) may have the best Quality Score Quality Score. Thus, it can be concluded that the quality of images significantly affects the perception of objects in a game environments, and combining quality methods can produce better results.

Using the Lab color space to calculate ΔE00 is methodologically sound and in line with modern approaches to assessing color perceptual accuracy, but using only the averaged ΔE00 value for the entire image may not be representative enough in the context of gamified visual environments. The average indicator well reflects the general trend of color differences, however, it smooths out local anomalies and can hide critical distortions in small but semantically significant areas of the image. In Gamified Systems, the user perceives the scene unevenly, focusing on the faces of the characters, textual elements of the interface, status indicators or rewards, so even slight color shifts in these areas can significantly affect the subjective quality of perception, while large homogeneous background areas with a low level of deviations reduce the overall average value and form a false impression of acceptable image quality.

In view of this, it is advisable to supplement the global average indicator with a local analysis of color differences in key regions of attention, as well as taking into account the peak or upper values of deviations, which makes it possible to detect critical distortions that are not manifested in the average statistical evaluation. Additional objectivity is provided by a weighted approach, according to which different areas of the image are given different importance according to their role in the user's interaction with the interface, which makes it possible to form an integral indicator closer to the real perceptual experience. Such a modification of the approach increases the sensitivity of the method to local color defects and makes the assessment more adequate to the specifics of gamified systems, where the crucial importance is not so much the averaged color accuracy over the entire frame, but the correct display of visually critical objects.

In practice, such an addition to the methodology gives, first of all, an increase in the reliability of the quality assessment and a better correspondence of the results with real user perception. When the analysis takes into account not only the average value over the entire frame, but also local deviations in the attention zones, the system stops “missing” critical color errors on character faces, text captions or status indicators. As a result, the assessment ceases to be formally statistical and acquires an applied meaning – it reflects not just the technical similarity of the images, but how they are actually seen and interpreted by the user during interaction with the interface or game scene.

For developers and designers, this means a more accurate content quality control tool during the testing and graphics optimization stages. Problem areas that affect the readability of the HUD, the emotional perception of the characters, or the correctness of the color signals of rewards and warnings can be quickly identified. In the production process, this reduces the risk of releasing interfaces with hidden visual defects, reduces the number of repeated redesign iterations, and allows finer tuning of compression, color correction, and rendering without losing significant details.

From the point of view of user experience, the practical effect is manifested in increased engagement, trust and ease of interaction. Locally correct colors on key objects reduce cognitive load, improve item recognition speed, and reduce the likelihood of errors in navigation or decision making in a game or educational platform. In the long term, this has a positive impact on user retention metrics, interface satisfaction, and the overall effectiveness of the gamified system, as the quality of the visual experience is directly related to motivation and engagement duration.

CONCLUSIONS

The developed technique is to combine two different approaches to the analysis of images: assessing the difference between colors using the Ciede2000 technique and evaluating the structural properties of the image using fractal analysis. The above mathematical model allows you to combine the Ciede2000 technique and fractal image analysis for evaluation, both color characteristics and structural features of the image. As a result of the combination of these two techniques, it allows you to get a more complete and comprehensive understanding of the quality assessment of a digital image. Based on the analysis of the hypotheses, it was established that the quality of images significantly affects the perception of objects in a game environment, and combining quality improvement methods can produce better results.

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Оцінка якості цифрового зображення візуальних об'єктів у гейміфікованих системах

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АНОТАЦІЯ

Стаття присвячена розробленню та обґрунтуванню комплексного підходу до оцінювання якості цифрових зображень у середовищах гейміфікації з урахуванням особливостей сприйняття візуальних об’єктів користувачами. Актуальність дослідження зумовлена зростанням ролі гейміфікованих візуальних інтерфейсів у цифрових застосунках і потребою в об’єктивному контролі якості візуального контенту, що безпосередньо впливає на рівень залученості та мотивації користувачів. У роботі проаналізовано сучасні методи оцінювання інформативності та якості цифрових зображень, зокрема підходи на основі текстурного аналізу, просторової структури, машинного навчання та глибоких нейронних мереж. Запропоновано гібридний метод, який поєднує оцінювання кольорових відмінностей за стандартом CIEDE2000 із фрактальним аналізом структурних характеристик зображень, що дає змогу враховувати як кольорові, так і геометрично-текстурні властивості візуальних об’єктів. Методологія дослідження ґрунтується на формулюванні та перевірці гіпотез щодо впливу якості оброблення зображень на сприйняття об’єктів у гейміфікованих середовищах, математичному моделюванні інтегрального показника якості з використанням вагових коефіцієнтів, а також програмній реалізації запропонованого підходу засобами Python. Практичне тестування виконано на наборі цифрових зображень різних рівнів графічної складності (прості, помірної складності та складні), для яких обчислено показники CIEDE2000, фрактальну розмірність, інтегральний індекс якості, а також метрики MSE і SSIM. Отримані результати підтверджують, що поєднання кольорового та структурного аналізу забезпечує повнішу й об’єктивнішу оцінку якості гейміфікованих зображень порівняно з використанням окремих методів. У роботі показано, що підвищення якості зображень статистично пов’язане з покращенням сприйняття візуальних об’єктів, а застосування комбінованого методу дає змогу коректніше диференціювати рівні якості для зображень різної складності. Запропонований підхід може бути використаний для автоматизованого контролю якості візуального контенту в комп’ютерних іграх, освітніх платформах та інших гейміфікованих системах, а також створює підґрунтя для подальших досліджень у напрямі адаптивного й інтелектуального оцінювання візуальних даних.

Ключові слова: зорове сприйняття; інформативність даних; відмінність кольору; фрактальна розмірність; інтегральний показник якості.

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