Designing an intelligent system for digital image classification*

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Abstract

Visual data volumes are growing exponentially due to the massive implementation of digital technologies, the development of social platforms, and the increasing availability of camera devices. The issue of automating the classification of digital images is significant. At the same time, it is important to determine the quality of images by key criteria. This innovative and theoretically grounded approach can improve classification results. Thus, the main goal of the article is to design an intelligent system for digital image classification based on machine learning methods and tools. The main research problem is the necessity to improve the accuracy of raster image classification, taking into account quantitative and qualitative characteristics — influence factors on the quality of images.

The topic highlights key factors affecting the quality of raster images. The method of expert evaluation was used to achieve this. The priority of factors is determined using the method of mathematical modeling of hierarchies, which consists of building a reachability matrix, considering influences and dependencies between factors, and creating the required number of iterative tables. The iteration results in the following distribution of factors by priority level: Level 1 belongs to the factors resolution and color model; Level 2 — to the factors color depth, file format and image size; Level 3 — compression, brightness, saturation; Level 4 — file size, sharpness. The model of the prioritized influence of factors on the quality of raster images has been developed, which is the basis for selecting digital data for further classification. Obviously, the classification accuracy directly depends on the quality of the images.

An intelligent system for classifying digital images was designed. In particular, the architecture of the intelligent system was developed. The class diagram is built to demonstrate the logic of interaction between the system components and the process of graphic information processing.

Thus, the formalized selection of relevant features that significantly affect the classification results is presented, and the interdependencies between them are determined. The developed concept of an intelligent system is based on the integration of machine learning methods with analytical models for assessing image quality. The obtained results of the study provide a scientifically grounded basis for selecting optimal image preprocessing methods, which helps to improve the accuracy, stability, and consistency of classification. The proposed system demonstrates high potential for practical application in various tasks of raster image analysis, providing effective processing of input data and adaptation to specific conditions of use.

Keywords

raster image, mathematical modeling of hierarchies, priority of factors, intelligent system, machine learning, digital image classification

1. Introduction

Modern research confirms the significant importance of digital images in different fields, including medicine [1, 2], education [3], architecture [4], printing [5], and others. For example, in medicine, digital images allow doctors to detect and diagnose diseases, injuries, and abnormalities with high

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accuracy. A comparison of images taken at different points in time shows treatment progress or disease relapse. In addition, digital images can be transferred via the Internet, making it possible for patients to consult with specialists worldwide [6]. The use of digital images in education contributes to improving the learning process and empowering both teachers and students by visualizing complex concepts, interactive learning, supplementing distance learning, and more effective assessment [7]. In architecture, digital images play a key role in creating detailed visualizations of projects, allowing architects and clients to better understand design and spatial solutions. They are also used for modeling and analyzing structures, ensuring accuracy and efficiency at all stages of construction, and helping promote architectural projects, making them more attractive to potential investors and customers [8]. In the publishing and printing industry, digital images are an integral part of most camera-ready mockups: books, booklets, albums, labels, etc., and their quality has a direct impact on the quality of finished printed products [9]. The above list is not exhaustive, indicating the research topic's great importance and relevance.

Artificial intelligence and machine learning are important links in the development of modern technologies [10]. Due to their efficiency and versatility, image processing and classification models have become particularly popular. They allow us to automatically analyze and categorize a range of visual data: faces in photos, road signs, medical images, CCTV footage, etc. [11, 12]. The rapid growth of visual information makes this prospect necessary [13, 14]. Classification, search, and analysis tools are constantly improving and can partially or completely eliminate this problem by organizing data for easy use.

Given that digital images are divided into several main types, which differ significantly in their properties and characteristics, it is reasonable to consider in this study one of the most widely used — raster images. Raster images consist of arrays of pixels (dots), each with a unique color and intensity value, and they are the smallest element of a raster image. These images have generally been captured or created using digital devices, such as cameras or scanners [15]. The quality of raster images is formed based on such parameters as resolution (a measure of detail or clarity of an image determined by the number of pixels per unit length or area), color depth (the number of bits used to encode the color of each pixel), a color model (determines the way colors are represented and combined, for example, RGB, CMYK, HSB, Lab, etc.), file format (how the image information is stored in the file, for example, JPEG, PNG, BMP, TIFF, etc.), file size (the amount of disk space taken by the image file), image size (the number of pixels in the width and height of the image), compression (the degree of file compression to reduce the size), brightness (a measure of the light intensity of a color that determines how light or dark the color tone will look), saturation (a measure of the purity and intensity of a color), sharpness (a characteristic that determines the clarity and detail of an image) [16, 17].

To ensure high accuracy of image classification it is necessary to consider their quality. The need to evaluate the quality of graphic material is due to the possible loss of quality at the stages of receiving, compressing, transmitting, and displaying a visual signal [18]. There are many objective and subjective approaches for image quality assessment, but most of them are based on analyzing the finished original, significantly slowing down the process of obtaining high-quality reproduction results. Subjective evaluation can be absolute and comparative. In absolute evaluation, the image is analyzed based on its own characteristics, while in comparative evaluation, the image is compared with others in a particular group, and the conclusion is formed based on its compliance with the group's indicators. This assessment depends on the external environment, including lighting, the quality of the information output devices (monitor, graphic tablet, etc.), the perception of the evaluator, etc. This approach requires significant time and the availability of professional experts. Objective evaluation, like subjective evaluation, can be absolute and comparative. Absolute evaluation is based on quantitative values of the parameters of a particular image, such as sharpness and contrast. The most common objective comparative methods are the mean squared error and peak signal-to-noise ratio. Additionally, comparison of sharpness, structural similarity for halftone images, etc., are also used [19]. In addition to classical methods, it is advisable to conduct a predictive assessment of the quality of digital images based on information about the factors that form them.

The advantage is the ability to adjust the input parameters based on the obtained forecast to achieve the desired level of quality [20, 21].

Thus, the study aims to design an intelligent system for classifying raster images based on machine learning methods and tools. The study's primary objectives are to build a model of the priority influence of factors on the quality of raster images to improve classification accuracy, develop a general architecture of an intelligent system for classifying digital images, and create a class diagram of the model execution process.

The proposed study is the initial stage of scientific research on predictive assessment of the quality and classification of digital images. Further prospects lie in the development, testing, and implementation of the designed intelligent system.

2. Literature review

Modern research on digital image quality assessment and classification utilizes various approaches that have their advantages and disadvantages.

In [22], a method for assessing digital image quality without a reference sample usage is proposed based on the statistics of feedforward neural networks. This approach allows for effective image quality assessment without needing access to the original. However, the method may have limited accuracy when processing images with atypical artifacts or distortions. Instead, our study is based on assessing image quality by key influence factors, making it possible to consider atypical situations.

Image classification by quality, using specialized detectors and recognizers for each quality class [23], allows to improve the accuracy of face recognition in images with different quality levels. The advantage is adaptability to different shooting conditions, but it requires training separate models for each quality class, which increases the system's complexity.

Paper [24] explores automated image quality assessment in medical applications, particularly in echocardiography. Generative adversarial networks were used to classify images by quality and improve diagnostic accuracy. This improved the objectivity and repeatability of assessments, but the method may require a large amount of graphical material for training and can be sensitive to data variations.

Study [25] focuses on modeling the image quality assessment process based on the relationship between visual images and human perception. IQA modeling plays a special role in combining vision science with engineering practice. The authors have presented a review of IQA methods from a Bayesian perspective to integrate a wide range of approaches into a single structure and provide useful references to fundamental concepts. However, it is important to emphasize the complexity of Bayesian models. The proposed approach may require significant computational resources, which limits its practical application.

In [26], an architecture is presented that uses pre-trained models for image feature extraction and then adapts these features to a specific classification task. The proposed approach can be applied to different types of images and classification tasks, making it flexible and suitable for various applications.

Compared to the analyzed ones, the advantages of our study are the construction of a detailed multilevel model of the priority influence of factors on the quality of digital images, which demonstrates how individual factors interact and influence each other, considering their levels of importance. This provides a more informed basis for optimizing image processing. In addition, image classification is integrated with text description generation. This extends the system's functionality compared to others focusing mainly on image classification or segmentation. A clear description of each stage of the system's operation (from data preparation to classification and text generation) makes it easy to adapt the proposed system to other areas or data types, which is a significant scientific contribution.

3. Material and methods

The study's initial stage is to identify the factors affecting the digital image quality, which directly affects the classification results. The formation of the set of factors $D = \{D_1, D_2, \dots, D_n\}$ is based on expert judgment, which allows us to identify the most significant parameters. Determining the relationships between factors involves establishing influences and dependencies [20].

To determine the levels of priority of factors, we used the method of mathematical modeling of hierarchies based on the relationships between the factors. The essence of the method is to build an accessibility matrix M, which contains binary elements that indicate the presence or absence of a relationship between the analyzed pair of factors. If there is a relationship between the two factors, the corresponding element of the matrix takes the value 1, which reflects their interaction. In the absence of a relationship, zero is indicated:

$$D_{ij} \begin{cases} 1, \; if \; it \; is \; possible \; to \; reach \; vertex \; j \; from \; vertex \; i; \\ \qquad\qquad 0, otherwise. \end{cases} \tag{1}$$

The accessibility of one factor $D_j (j = 1,2, \dots, n)$ to another $D_i (i = 1,2, \dots, n)$ is determined based on interconnections identified by the expert method. The subset of factors that can be reached from a particular vertex forms the set of its reach $K(D_i)$. At the same time, a subset of factors for which a given factor is reachable forms the set of predecessors $P(D_i)$. The intersection of these sets determines the group of factors with a dominant influence, which is established through the analysis of iteration tables:

$$H(D_i) = K(D_i) \cap P(D_i), \tag{2}$$

where $H(D_i) = P(D_i)$.

Each table contains an ordered list of factors and a set of characteristics that define their role in the general structure of relationships. The data required to build the iterative tables is generated from the information in the reachability matrix: the matrix rows define the set of reachable factors, and the columns establish the set of predecessors. The common factors in both sets form a group of interrelated factors directly affecting the quality of digital images.

As a result of computational operations, a multilevel model is formed that reflects the priority of the influence of individual factors on the quality of digital images [20, 21].

Raster images are classified and described using machine learning methods that allow computers to learn and make data-based decisions. These methods are divided into several categories depending on the task's character and the type of data available [10-12]. The main approaches in machine learning are supervised, unsupervised, reinforcement, and semi-supervised (Fig. 1).

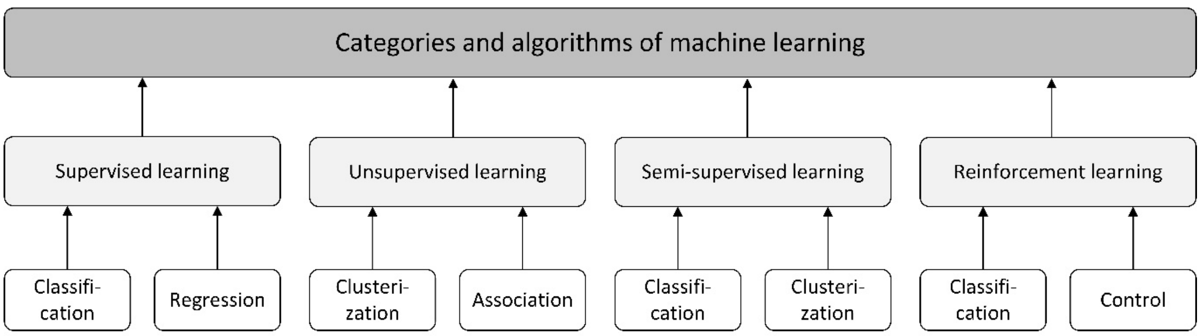

Figure 1: Classification of machine learning categories and algorithms.

Supervised learning uses labels for each sample in the dataset. The algorithm analyzes input data and learns to predict the correct output values. The main task is to identify dependencies between input and output parameters. Unsupervised learning does not require labeled data. The algorithm identifies structures and patterns in the dataset. It is often used for clustering and dimensionality reduction. Semi-supervised learning combines approaches from both supervised and unsupervised learning. The algorithm utilizes a small amount of labeled data along with a large amount of unlabeled data. This approach improves model accuracy while requiring limited resources. Reinforcement learning is based on the interaction of an agent with the environment. The agent receives rewards or penalties depending on its actions. The primary goal is to maximize cumulative reward.

When designing an intelligent system, the process of executing classification and description models based on machine learning methods consists of six main stages:

1. Initialize parameters and paths: define configurations, set paths to input data, and set parameters to save results.
2. Image pre-processing: uploading images, analyzing them by key factors, considering their priority, and processing (resizing, normalization, etc.).
3. Image classification: analyzing and determining the appropriate category. If the image corresponds to a particular class, the categorization continues. Otherwise, the stage ends and moves to the next one. Depending on the number of classes, classification can repeat several times.
4. Creating description: The image is transferred to the description generation model, which uses a pre-trained neural network to extract its vector features.
5. Description generation: The allocated image properties are transferred to the text part of the model, which forms the image description.
6. Obtaining results: The output information containing the defined image classes and their descriptions is transformed into data that can be stored, displayed, or transferred for further processing.

Thus, the cycle combines the functionality of at least two different models, ensuring not only automatic image category detection but also the creation of a detailed text description to help better understand the content.

4. Experiment, results and discussion

Expert evaluation methods have been used to establish a set of factors affecting the quality of raster images: $D = \{D_1, D_2, D_3, D_4, D_5, D_6, D_7, D_8, D_9, D_{10}\}$, where D_1 — resolution, D_2 — color depth, D_3 — color model, D_4 — file format, D_5 — file size, D_6 — image size, D_7 — compression, D_8 — brightness, D_9 — saturation, D_{10} — sharpness.

The links between the factors are demonstrated using the following structural elements: «$\wedge$» — logical AND; «$\rightarrow$» — the presence of direct influence; «$\rightarrow$ ( )» — the presence of indirect influence; «$\leftarrow$» — the presence of direct dependence; «$\leftarrow$ ( )» — the presence of indirect dependence; «$\leftrightarrow$» — no influence or dependence on other factors [10].

The influence factors are as follows:
$D_1 \rightarrow D_5 \wedge D_1 \rightarrow D_6 \wedge D_1 \rightarrow (D_5) \wedge D_1 \rightarrow D_{10}$; $D_2 \rightarrow D_5 \wedge D_2 \rightarrow D_8 \wedge D_2 \rightarrow D_9$; $D_3 \rightarrow D_2 \wedge D_3 \rightarrow (D_5, D_8, D_9) \wedge D_3 \rightarrow D_4 \wedge D_3 \rightarrow (D_5, D_7, D_8, D_{10}) \wedge D_3 \rightarrow D_9$; $D_4 \rightarrow D_5 \wedge D_4 \rightarrow D_7 \wedge D_4 \rightarrow (D_5, D_{10}) \wedge D_4 \rightarrow D_8 \wedge D_4 \rightarrow D_{10}$; $D_5 \leftrightarrow D_5$; $D_6 \rightarrow D_5$; $D_7 \rightarrow D_5 \wedge D_7 \rightarrow D_{10}$; $D_8 \leftrightarrow D_8$; $D_9 \leftrightarrow D_9$; $D_{10} \leftrightarrow D_{10}$.

Factor dependencies:

$D_1 \leftrightarrow D_1$; $D_2 \leftarrow D_3$; $D_3 \leftrightarrow D_3$; $D_4 \leftarrow D_3$; $D_5 \leftarrow D_1 \wedge D_5 \leftarrow D_2 \wedge D_5 \leftarrow (D_3) \wedge D_5 \leftarrow D_4 \wedge D_5 \leftarrow (D_3) \wedge D_5 \leftarrow D_6 \wedge D_5 \leftarrow (D_1) \wedge D_5 \leftarrow D_7 \wedge D_5 \leftarrow (D_4)$; $D_6 \leftarrow D_1$; $D_7 \leftarrow D_4 \wedge D_7 \leftarrow (D_3)$; $D_8 \leftarrow D_2 \wedge D_8 \leftarrow (D_3) \wedge D_8 \leftarrow D_4 \wedge D_8 \leftarrow (D_3)$; $D_9 \leftarrow D_2 \wedge D_9 \leftarrow (D_3) \wedge D_9 \leftarrow D_3$; $D_{10} \leftarrow D_1 \wedge D_{10} \leftarrow D_4 \wedge D_{10} \leftarrow (D_4) \wedge D_{10} \leftarrow D_7 \wedge D_{10} \leftarrow (D_4)$.

The method of mathematical modeling of hierarchies was used to determine the priority levels of the identified factors. According to (1), a matrix of the availability of factors influencing the quality of raster images was constructed. For convenience, it is presented in tabular form (Table 1).

Table 1
The reachability matrix of factors influencing the quality of digital images

Factors	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}
D_1	1	0	0	0	1	1	0	0	0	1
D_2	0	1	0	0	1	0	0	1	1	0
D_3	0	1	1	1	1	0	1	1	1	0
D_4	0	0	0	1	1	0	1	1	0	1
D_5	0	0	0	0	1	0	0	0	0	0
D_6	0	0	0	0	1	1	0	0	0	0
D_7	0	0	0	0	1	0	1	0	0	1
D_8	0	0	0	0	0	0	0	1	0	0
D_9	0	0	0	0	0	0	0	0	1	0
D_{10}	0	0	0	0	0	0	0	0	0	1

Iterative tables (Tables 2–5) were created using the data presented in the reachability matrix. If the data in the third and fourth piles coincide, the priority of the factors is considered to be determined.

Table 2
First level of iteration

i	$K(D_i)$	$P(D_i)$	$K(D_i) \cap P(D_i)$
1	1, 5, 6, 10	1	1 ⟵
2	2, 5, 8, 9	2, 3	2
3	2, 3, 4, 5, 7, 8, 9	3	3 ⟵
4	4, 5, 7, 8, 10	3, 4	4
5	5	1, 2, 3, 4, 5, 6, 7	5
6	5, 6	1, 6	6
7	5, 7, 10	3, 4, 7	7
8	8	2, 3, 4, 8	8
9	9	2, 3, 9	9
10	10	1, 4, 7, 10	10

Table 3
Second level of iteration

i	$K(D_i)$	$P(D_i)$	$K(D_i) \cap P(D_i)$
2	2, 5, 8, 9	2	2 ⟵
4	4, 5, 7, 8, 10	4	4 ⟵
5	5	2, 4, 5, 6, 7	5
6	5, 6	6	6 ⟵
7	5, 7, 10	4, 7	7
8	8	2, 4, 8	8
9	9	2, 9	9
10	10	4, 7, 10	10

Table 4
Third level of iteration

i	$K(D_i)$	$P(D_i)$	$K(D_i) \cap P(D_i)$
5	5	5, 7	5
7	5, 7, 10	7	7 ⟵
8	8	8	8 ⟵
9	9	9	9 ⟵
10	10	7, 10	10

Table 5
Fourth level of iteration

i	$K(D_i)$	$P(D_i)$	$K(D_i) \cap P(D_i)$
5	5	5	5 ⟵
10	10	10	10 ⟵

According to the results of the iteration, the following distribution of factors by priority levels was obtained: 1st level: D_1 — resolution, D_3 — color model; 2nd level: D_2 — color depth, D_4 — file format, D_6 — image size; 3rd level: D_7 — compression, D_8 — brightness, D_9 — saturation; 4th level: D_5 — file size, D_{10} — sharpness.

Respectively, the model of the priority influence of factors on digital (raster) image quality has the form (Fig. 2):

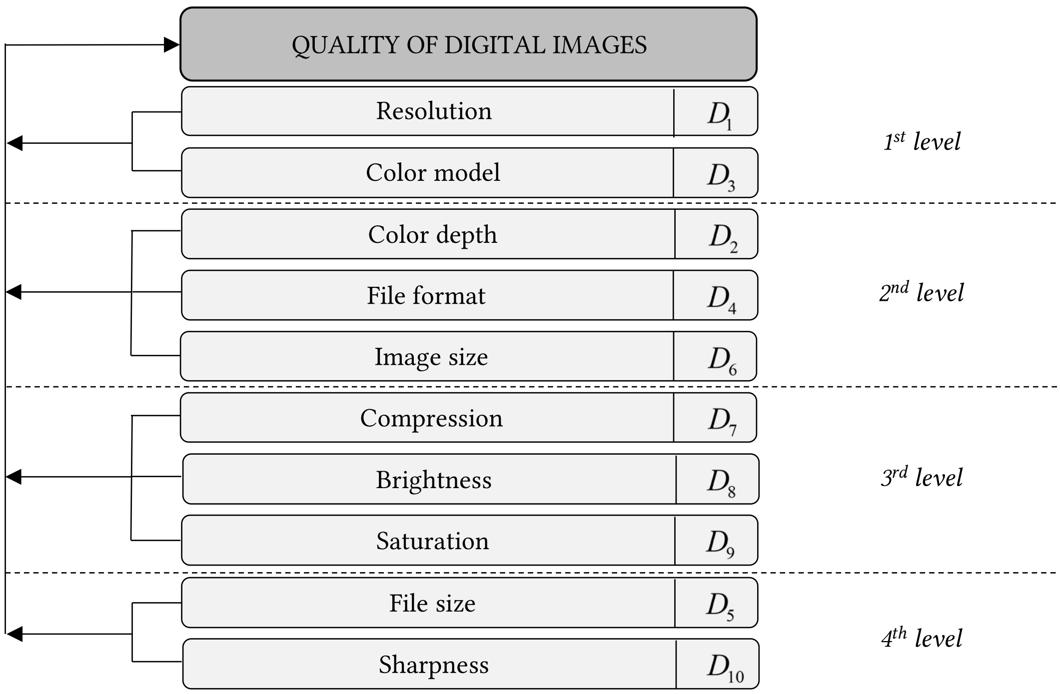

Figure 2: Model of the priority influence of factors on the quality of digital images.

Modeling the priority influence of factors facilitates a reasonable choice of pre-processing and analysis methods, which is necessary to improve the accuracy and stability of classification. The developed model of the priority influence of factors makes it possible to select high-quality images for further classification. Therefore, the next stage of the study is to design the architecture of an intelligent raster image classification system (Fig. 3).

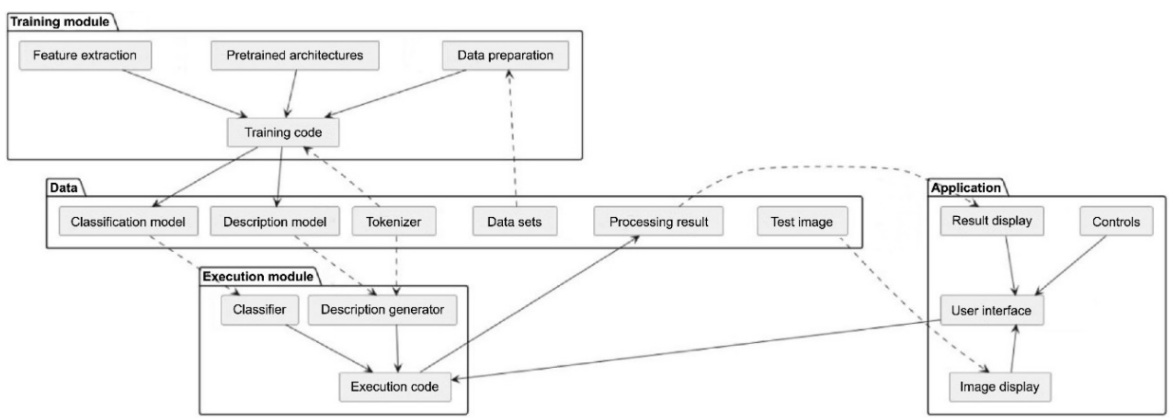

Figure 3: Architecture of an intelligent digital image classification system.

The system architecture consists of four main components: the application, the data subsystem, the training module, and the execution module. Each serves specific functions that provide the integrated operation of the system for image processing and analysis.

The application serves as the main interface for user interaction with the system. Its functional structure includes a user interface that provides data entry, data management, and display of the computing process's results. The main element of interaction is the image screen for loading graphical data. The results screen visualizes the final characteristics of the processing, including the classification and text description of the images. The main operations (input data loading, results cleaning, and processing initiation) are performed due to interactive controls.

The data subsystem includes training sets containing graphical objects with corresponding textual annotations necessary for efficient model training. The tokenizer transforms textual descriptions into vectorized representations used in text generation processes. The classification model implements algorithmic mechanisms for determining the image category. The description model forms text annotations based on graphical characteristics. The input test images serve as empirical material for evaluating the system's accuracy, and the processing results contain both classification characteristics and textual descriptions provided to the user. Thus, the system operates based on interdependent processes that ensure a holistic operation.

The training module contains algorithmic tools to build, train, and optimize classification models and generate text descriptions. Its functionality provides mechanisms for data preparation: transformation and adaptation of training sets for their further use in modeling processes.

The execution module is responsible for computational operations and implements image analysis algorithms. The execution code guarantees the integration and coordination of all processing activities. An important module element is the classifier, which implements mechanisms for categorizing input graphic data according to certain parameters, such as image types. Additionally, the module structure includes a description generator that uses analytical characteristics of the input image to generate text descriptors automatically. Its operation is based on using a tokenizer that transforms text data into a format suitable for further processing by neural network models.

For a better understanding of the program's component architecture, a class diagram has been created (Fig. 4).

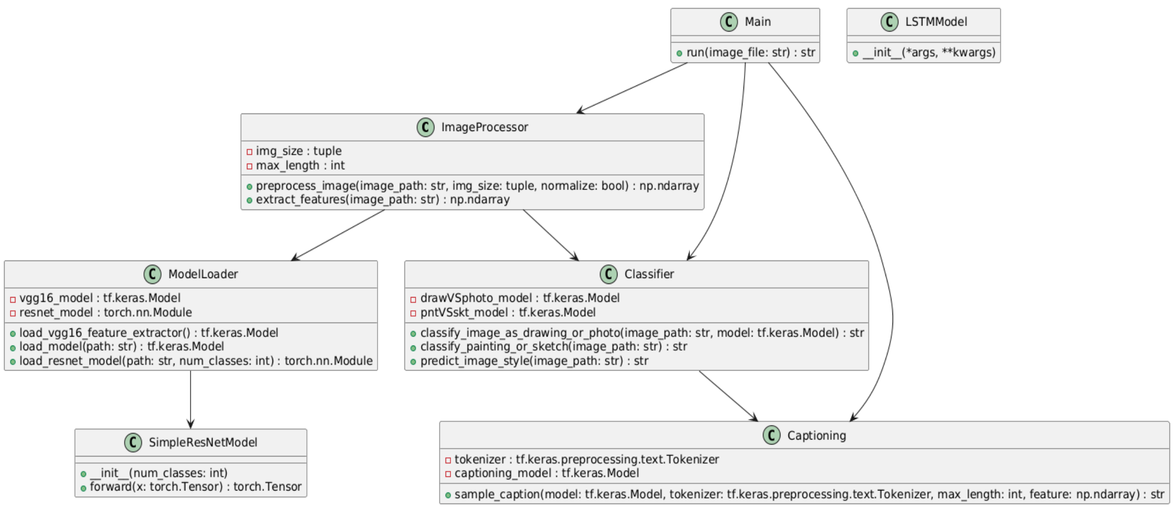

Figure 4: Class diagram of an intelligent digital image classification system.

In the initial step, necessary libraries are imported to work with models, images, and text data. Next, the system checks for the presence of an input image passed via the command line. In case if the argument is missing or the corresponding file cannot be found, the system generates an error message and stops execution. If the image is loaded correctly, the system proceeds to the main processing procedures, predefining global variables that contain paths to models and files required for further analysis stages.

The next step is to initialize the utility functions. One function loads and preprocesses the input image, preparing it for classification. Another function loads the model, which is used to extract features from images. Additionally, pre-trained models are loaded to divide images into categories and classify them into subcategories.

At the final stage, a tokenizer and a model for generating image captions are applied. Data is extracted from the graphic object to create a text description automatically. The signature generation is based on the mechanism of long short-term memory.

As a result, the program structure generates and outputs results that contain all the defined categories and the generated text description for the input image.

Thus, the study made it possible to build a model of the priority influence of factors on the quality of digital raster images. The formation of a set of factors and the relationships between them was carried out using an expert evaluation method, which provided a holistic view of each factor's influence. This approach made it possible to identify key parameters that should be considered at the image processing stage, in particular, resolution and color model as factors of the first priority level. Resolution is a fundamental characteristic of an image. It indicates the number of discrete elements per unit length or the total number of pixels in an image. This parameter plays a crucial role in digital graphics, printing, and computer vision. It is also a key factor in any processes related to visual data processing. A color model is a mathematical representation of colors in the form of numerical values. It defines color parameters within a specific color space. The most widely used models are RGB, CMYK, and HSV.

The proposed architecture of an intelligent digital image classification system covers all processing stages, from data loading to text description generation. Using tokenizer and long short-term memory models ensures the high-quality generation of text annotations based on image graphical features. The integration of the execution, training, and data subsystem modules is important, allowing the system to work as a whole.

The study results can be used to optimize graphic data processing methods in practical image classification tasks. In addition, the proposed system provides automation of the processes of creating textual descriptions, which is important for increasing the efficiency of working with large volumes of digital images. Prospects for further research are to improve the training algorithms and expand the functionality of the system and its practical implementation.

5. Conclusions

A set of factors influencing the quality of digital images is identified: D_1 — resolution, D_2 — color depth, D_3 — color model, D_4 — file format, D_5 — file size, D_6 — image size, D_7 — compression, D_8 — brightness, D_9 — saturation, D_{10} — sharpness. The priority of the factors is determined by the method of mathematical modeling of hierarchies, which allows to systematize their influence and optimize the methods of analysis. A multilevel model of the priority influence of factors on the quality of digital raster images has been developed. Based on the results of the iterative analysis, four levels of priority of factors influencing the quality of digital images were identified: Level 1 — factors resolution and color model; Level 2 — factors color depth, file format and image size; Level 3 — compression, brightness, saturation; Level 4 — file size, sharpness. That is, the highest priority level belongs to the factors resolution and color model. The obtained model allows for systematizing the influence of these factors and optimizing the choice of parameters to improve the classification quality. In this case, the highest level of priority belongs to the factors resolution and color model.

The architecture of an intelligent digital image classification system was developed, consisting of four main components: an application, a data subsystem, a training module, and an execution module. The application is used for user interaction with the system. The data subsystem contains training sets with graphical objects and corresponding text annotations necessary for the system's accuracy. The training module is designed to prepare, train, and optimize classification models and generate text descriptions. The execution module provides image analysis, automatic generation of text descriptions, and categorization based on graphical features.

A class diagram was built, which illustrates the logic of interaction between system components and image processing procedures. The results of the study allow us to reasonably choose methods of image preprocessing, increasing the accuracy and classification stability. The developed system has the potential to be used in practical tasks of raster image analysis.

The limitation of this study is that the proposed model of the priority influence of factors is based on expert evaluation, which causes a certain subjectivity in determining the weight of individual characteristics. In addition, the method of mathematical modeling of hierarchies involves a small number of iterations, which may affect the accuracy of the final distribution of factors by priority levels. Also, the developed system is oriented to the analysis of raster images only, which limits its application to vector graphics or complex multilayer images. The main directions for further research are: refinement of the weight values of the factors influencing the quality of raster images using the ranking method; expanding the functionality of the proposed intelligent system by integrating deep neural networks; adapting algorithms to vector graphic formats; developing and testing the system on sets of images of different nature to assess the effectiveness in conditions of heterogeneous data.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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