UDC 303.732.4 + 004.67 + 004.8
DOI: 10.20535/SRIT.2308-8893.2022.4.05

THE PROBLEM OF AUTOMATIC CLASSIFICATION OF PICTURES USING AN INTELLIGENT DECISION-MAKING SYSTEM BASED ON THE KNOWLEDGE GRAPH AND FINE-GRAINED IMAGE ANALYSIS

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Abstract. In order to prevent the illegal export of paintings abroad, a museum examination using various methods for studying a work of art is carried out. At the same time, an analysis is also made of historical, art history, financial and other information and documents confirming the painting's authenticity — provenance. Automation of such examination is hampered by the need to take into account numerical values of visual features, quality indicators, and verbal descriptions from provenance. In this paper, we consider the problem of automatic multi-task classification of paintings for museum expertise. A system architecture is proposed that checks provenance, implements a fine-grained image analysis (FGIA) of visual image features, and automatically classifies a painting by authorship, genre, and time of creation. Provenance is contained in a knowledge graph; for its vectorization, it is proposed to use a graph2vec type encoder with an attention mechanism. Fine-grained image analysis is proposed to be performed using searching discriminative regions (SDR) and learning discriminative regions (LDR) allocated by convolutional neural networks. To train the classifier, a generalized loss function is proposed. A data set is also proposed, including provenance and images of paintings by European and Ukrainian artists.

Keywords: automatic multi-task classification, knowledge graph, attention mechanism, fine-grained image analysis, museum expertise, paintings, convolutional neural networks.

INTRODUCTION

The problem of art objects illegal export continues to be relevant, since they are a means of accumulating value. In Ukraine, normative documents that regulate the procedure for customs control and examination of cultural property have been adopted [1–6]. These documents establish and approve the procedure according to which it is possible to export values abroad, for which the Authority for Control over the Movement of Cultural Property and the Protection of the Cultural Heritage of Ukraine issued a certificate for the right to export. At the same time, basis for such a certificate is customs and museum expertise. The customs examination, first, aims to establish painting age, since, according to mentioned regulatory documents, antiques prohibited for export, include items over 100 years old. During the museum examination, the authenticity and authorship of painting is established, which, of course, also serves the purpose of dating the work of art.

A wide range of approaches used to establish paintings authenticity, include forensic, technological, attributive and other methods. They involve various forms of research, for example, study of artist's fingerprints, signatures, seals, lists of invoices confirming the painting sale, reproductions in books and catalogs, a description of the history of painting creation and ownership to the present moment (provenance). Experimental studies also include researching of paintings using microscopy, fluoroscopy, macrophotography, spectroscopy, etc.

Conducting such a comprehensive study takes a lot of time, requires the participation of dozens of highly qualified art historians, chemists, digital technology specialists.

Under conditions of a customs check, it is impossible to implement such an examination. Therefore, for prompt decision-making on a work of art exporting possibility, an intelligent decision-making system was proposed [7–9]. It provides for automatic identification of a painting and the establishment of its authenticity and value based on a photo. However, such an operational check is one part of the proposed two-stage procedure — it can only prevent the export of suspicious art values, but cannot replace a full museum expertize, which is the basis for a permit certificate.

It is possible to speed up an export permit by automating a full museum examination, which, from the point of view of machine learning, can be represented as a classification task. Research in this direction has been going on for many years, and in recent years, there has been a certain breakthrough associated with the use of deep networks, in particular, Convolutional Neural Networks (CNN). They are distinguished by ability to automatically generate vectors of non-obvious features, especially in image processing tasks, provide higher classification accuracy compared to other machine learning methods, and have high speed. Many works demonstrate that the application of CNN to automatic paintings classification gives positive results [10–14].

However, as noted, an important component of museum expertise is the study of painting's provenance, which is usually presented as textual descriptions of changing size. For CNN that analyze a painting image, provenance turns out to be useless. On the other hand, deep networks that have proved to be highly effective in word processing tasks, such as LSTM (Long Short-Term Memory), do not allow tracking signs of a correlation nature in two-dimensional signals – paintings photos.

Thus, the purpose of this work is to develop the architecture of an intelligent decision-making system based on deep networks for automatic classification of paintings, taking into account their provenance.

ANALYSIS OF AREAS OF RESEARCH AND STATEMENT OF THE PROBLEM

Deep networks are currently a common tool for solving a variety of data analysis problems: searching for objects in images and videos, automatic translation, handwriting recognition, processing streaming information. There are also examples of deep architectures use for solving various tasks of preserving cultural heritage in general [15–16], and paintings in particular. Thus, convolutional neural networks have been used to automatic paintings classification by author and artistic genre [10, 12, 14, 17, 18]. The initial data was digital paintings images, based on analysis of which CNN generates a response about painting authorship with high accuracy. At the same time, the classification attributes are formed automatically by the input layers of the CNN, and form internal descriptions – embeddings, "understandable" network parameters in numerical form. It is important to note that specially created datasets are used to train such networks, including tens of thousands of paintings images [19, 20]. However, the list of artists whose paintings are included in such sets is quite narrow and is limited to three to four dozen world-famous masters who worked during the 15th–20th centuries. In the course of training on such datasets, CNN studies the features of artists' writing and is able to quite accurately distinguish between paintings of different styles, but of the same master, or vice versa, of different authors, but of the same genre.

The works of artists included in the typical datasets used to train CNN are world masterpieces, their location is known, they are well protected. Therefore, the probability of their presentation for export from Ukraine is extremely small. However, there are a large number of paintings by lesser-known masters in the country that should be banned from export due to their significant value. These pictures were not used to train deep networks, so there is no guarantee that such a network will confirm the authorship with sufficient accuracy. An unequivocal help in this situation can be such an architecture that will allow using information about paintings provenance. In particular, in [19] it is proposed to use the Knowledge Graph for a provenance branched formalized description in the form of a graph structure available for further implementation using deep networks.

On the other hand, Ukrainian artists, whose works are of value and may be banned for export, worked for a much narrower period of time – during the 17th–20th centuries (those created no later than 1920 can be recognized as antiques). Due to historical circumstances, these paintings do not differ in genre and stylistic diversity, so it is possible that a network trained to distinguish between Renaissance and abstract art will not be able to accurately distinguish between landscapes painted in the style of 19th century classicism and early 20th century realism. The emerging field of machine intelligence Fine-Grained Image Analysis (FGIA) develops methods for analyzing sub-categories of images in a single meta-category [21, 22]. These methods are focused on finding more subtle and little noticeable, but significant (from authorship point of view) differences between images, which allow us to single out stable subclasses within the same class of objects.

In this paper, we propose to apply the Knowledge Graph to formalize provenance and use it as an attribute when categorizing paintings using Fine-Grained Image classification implemented in deep learning architecture.

METHODOLOGY

Representation of provenance

Information about painting creation history, its sale to past and current owners is an undoubted and weighty confirmation of authenticity, along with such characteristics as features of strokes, coloring, chemical composition of paints, primers, canvas and stretcher wood. This information can be quite scattered, since documents confirming it can be stored in various institutions, by different persons, or even be lost. Therefore, provenance data does not have a standardized format, and is represented most often by field's text entries such as [23]:

– author's name;
– artist's life years;
– picture name;
– picture creation date;
– technique (oil on canvas, oil on wood, watercolor, etc.);
– current location;
– URL link with a digital photo of the painting;
– form (painting, sculpture);
– type (portrait, still life, etc.);

– school (French, Dutch, etc.);

– era (years of the artist's work).

Examples of such records [23]:

TOULOUSE-LAUTREC, Henri de, "(b. 1864, Albi, d. 1901, Château Malromé, Langon)", Countess Adèle de Toulouse-Lautrec in the Salon of Malromé Château, 1887, "Oil on canvas, 54×45 cm", "Musée Toulouse-Lautrec, Albi", https://www.wga.hu/html/t/toulouse/2/1misc02.html, painting, portrait, French, 1851–1900.

UNKNOWN MASTER, German, (active 1490s in Nuremberg), Portrait of a Man, 1491, "Oil on linden panel, 37×20 cm", "Metropolitan Museum of Art, New York", https://www.wga.hu/html/m/master/zunk_ge/zunk_ge4a/portrman.html, painting, portrait, German, 1451–1500.

MONET, Claude, "(b. 1840, Paris, d. 1926, Giverny)", Monet's Garden at Argenteuil, 1873, "Oil on canvas, 61×82 cm", Private collection, https://www.wga.hu/html/m/monet/03/argent08.html, painting, landscape, French, 1851–1900.

In Ukraine, work is underway to catalog museum collections and draw up Scientifically Unified Passports. Although it is far from complete, it is being carried out in accordance with international experience (ICOM requirements, UNESCO Model export sertificate for cultural objects, etc.) [24].

A record about a painting can be represented as a graph, which in [19] is called the Knowledge Graph and displays elements of description of painting and the relationship between these elements. Taking into account Ukraine conditions, the structure is proposed to be modified (Fig. 1).

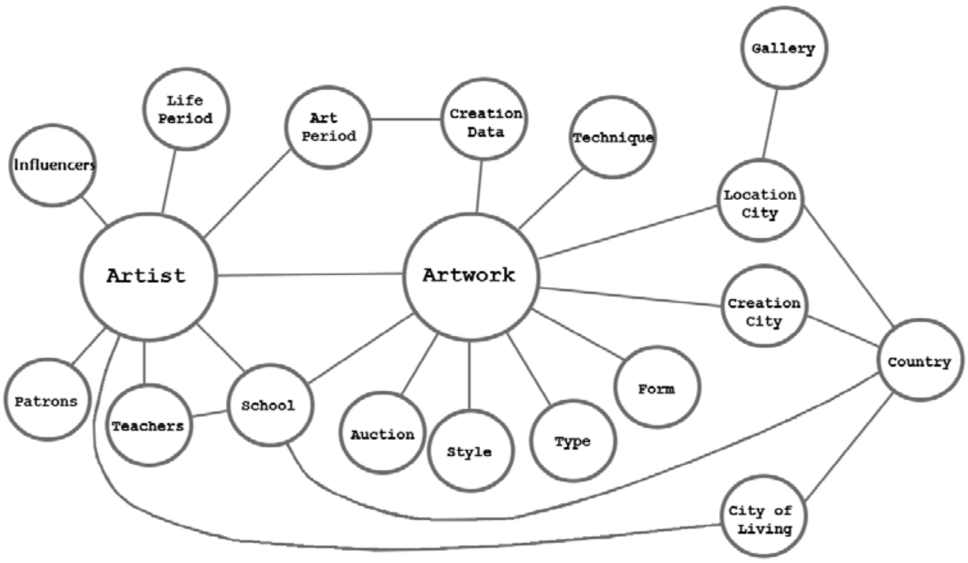

Fig. 1. Nodes and edges of a knowledge graph modeling metadata about a picture

Graph embeddings are extracted from model using an encoder – a pre-trained CNN that implements the node2vec transformation [25] and solves the task of classification a picture by provenance attributes represented as a graph model.

At present, networks such as ResNet50, ResNet101, ResNet152 demonstrate the highest classification accuracy in such problems [26, 27]. It is proposed to train network using a loss function [20]:

$$L_{\Pr ovenance}(p_j, u_j) = \left\| p_j - u_j \right\|_2^2,$$

where p_j — predicted embedding; u_j — ground truth context embedding; j — expertize object (painting).

Using Fine-Grained Image Analysis to paintings classification

Even experienced art historians sometimes make mistakes when determining the authorship or dating of works painted in the same style in a short time period. In addition to results of chemical, spectroscopic, and X-ray studies, the FGIA approach can help in solving this problem, which makes it possible to use information about difference in fine details of objects belonging to the same class. The main difficulty in approach implementing is preservation of information about regional features when network learns from hundreds of thousands of sample images. The attention mechanism allows finding the most significant regional features in images, and save information about them, despite large size of training datasets.

In [28], it is proposed to form special regions that store information about individual objects features belonging to subclasses – Searching and Learning Discriminative Regions (SDR, LDR).

Just as global features are extracted from images using a CNN and images are assigned to classes based on the mapping of these feature vectors, in discriminative regions, the deep network generates feature vectors within individual parts of images that are in some sense similar to each other. An example of such tasks is distinction between aircraft by type, birds by subspecies within the same family, and so on. The resulting vector includes both global features inherent in class images, and private (partial) inherent in subclass images.

Searching Discriminative Regions (SDR) are designed to search and locate particular features in an image. The scheme of search areas formation is shown in Fig. 2 [28].

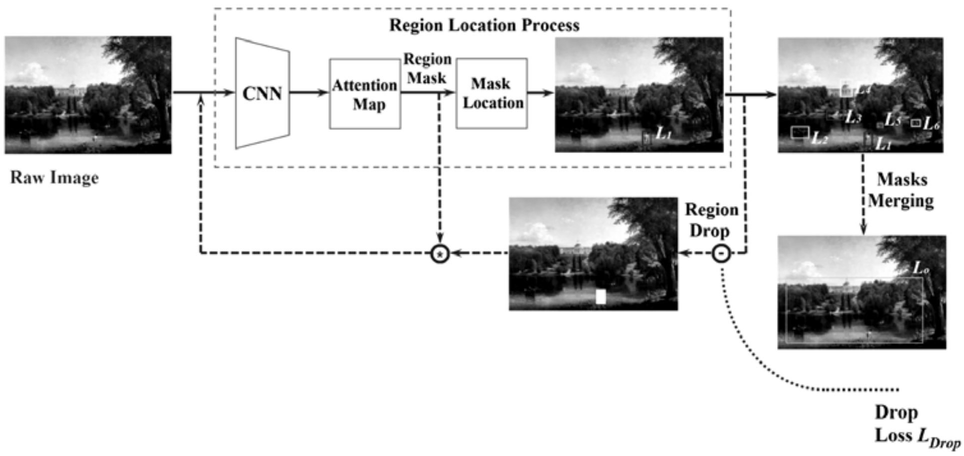

Fig. 2. Scheme of searching discriminative regions formation

At the heart of this system block operation is an attention-based search mechanism. The convolutional neural network here provides for search and selection of all possible features in image, and only thanks to the attention function does it become possible to search for heterogeneous characteristic features $L_1, L_2,..., L_n$ in one image, and use them as references for searching pictures in other images.

The network is trained to minimizing the objective function that describes the angular measure $\cos\theta_y$ of differences between actual categories logits (features) and their values predicted by network:

$$L_{arc} = -\log \frac{\exp(s(\cos\theta_y))}{\sum_{j=1, j\neq y}^{C} \exp(s(\cos\theta_j)) + \exp(s(\cos\theta_y))},$$

where C is the number of categories to classify. In this problem, it is equal to number of compared paintings in dataset.

When locating searching regions on image, it is necessary to minimize losses associated with excluded zones characteristics:

$$L_{Drop} = \sum_{i=1}^{n} L_{drop-arc}(C_d(em_{d_i})), \quad (1)$$

where em_{d_i} — image features generated by network that do not go beyond the network (embeddings) d_i, $i = 1,...,n$ associated with input picture; C_d — is a classifier that maps embeddings into classification objects (logits) categories features.

After searching regions finding, we need to compose their descriptions, taking into account their possible appearance in other dataset images. For this purpose, learning discriminative regions (LDR) are formed on basis of SDR, in accordance with scheme of Fig. 3.

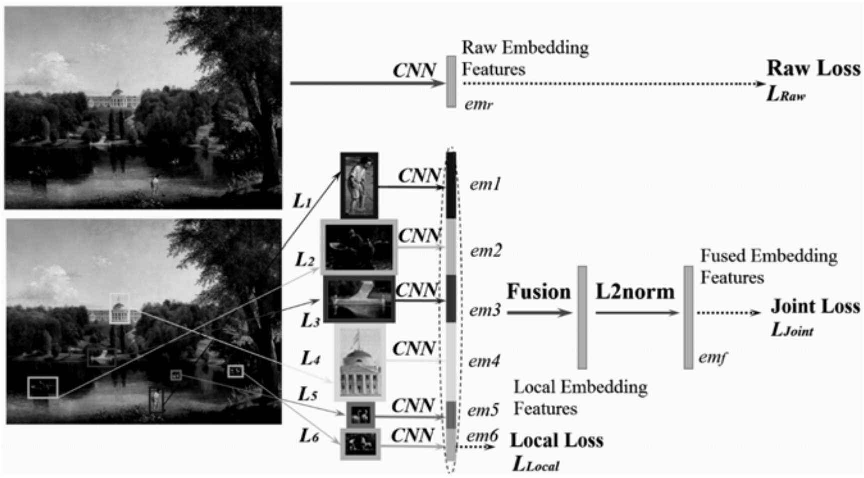

Fig. 3. Approach to LDR formation

By analogy with (1), loss functions are determined for training of convolutional networks that form embeddings $em_r, em_1,..., em_6,..., em_{d_m}, em_f$:

$$\begin{cases} L_{Raw} = L_{Raw-arc}(C_r(em_r)); \\ L_{Local} = \sum_{i=1}^{n} L_{Local-arc}(C_l(em_l)); \\ L_{Joint} = L_{Joint-arc}(C_f(em_f)), \end{cases}$$

where $em_r, em_1,..., em_6,..., em_{d_m}, em_f$ – embeddings associated with individual SDRs that are highlighted on input image; C_r, C_l, C_f – classifiers that map embedding features into category features (logits).

Local regional features (embeddings) are combined in Fusion module, forming a generalized vector em_f :

$$em_f = Fusion(em_r, em_1, ..., em_6, ..., em_{d_m}) .$$

Merge can be implemented by concatenation or convolution. In the second case, a 1D convolutional layer with H channels will need to be added to the network architecture, then dimension of generalized embedding vector will be $(n+2)H$.

Architecture of an automatic system for classifying paintings using Knowledge Graph and Fine-Grained Image Analysis

To solve the paintings classification problem, taking into account provenance in vector representation, and with possibility of distinguishing features of artists of the same genre, one time period, a system is proposed that is built using knowledge representation in the form of a graph structure, where feature extraction on images of paintings is performed using SDR and LDR .

The system general architecture is shown in Fig. 4. The main idea is to learn convolutional network to project metadata about picture and its fine-grained features into classification objects space. The solution is carried out in a multi-task mode due to concatenation of visual feature embeddings from original image, provenance embeddings from encoder, and fine-grained feature embeddings from SDR and LDR.

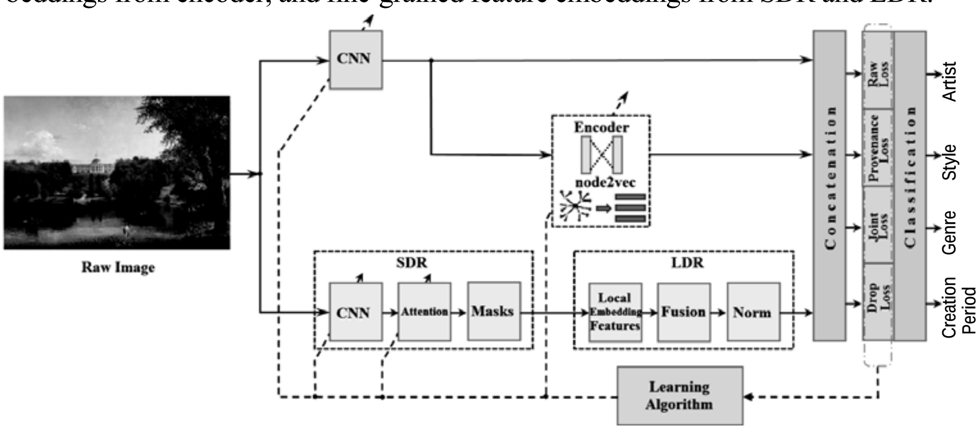

Fig. 4. Architecture of an automatic system for classifying paintings using Knowledge Graph and Fine-Grained Image Analysis

The system loss function in multitasking classification mode is defined as

$$L = (1-\gamma)\left(\lambda_{Raw} \sum_{j=1}^{N} L_{Raw-arcj}(C_r(em_r))(C_r(em_r)) + \right.$$

$$+ \lambda_{Joint} \sum_{j=1}^{N} L_{Joint-arcj}(C_f(em_f)) + \lambda_{Local} \sum_{j=1}^{N} \sum_{i=1}^{n} L_{Local-arcj}(C_l(em_i)) +$$

$$\left. + \lambda_{Drop} \sum_{j=1}^{N} L_{Drop-arcj}(C_f(em_{if})) \right) + \gamma \frac{1}{N} \sum_{j=1}^{N} L_{Provenance}(p_j, u_j) ,$$

where γ are error weights of system modules, λ_i are hyperparameters that takeinto account individual tasks contribution to classification result.

Datasets for solving the automatic paintings classification problem

Since provenance in this task is an integral part of initial information array, it is necessary to select data for system learning in an appropriate way. Many world-famous museums include metadata in verbal descriptions form when digitizing paintings. There are no detailed lists of all documents that verify the entire picture sale history in such descriptions, but even brief information about the time, place of creation, style, genre, school, etc. will increase accuracy of multitasking classification.

In this paper, it is proposed to use datasets [23, 29] that are freely available. They contain images of paintings by world masters who worked in 15th–20th centuries, in various techniques, styles and genres. In addition, these datasets contain brief information related to provenance.

To apply developed system in Ukraine, it is obviously necessary to supplement these sets with images of paintings by Ukrainian artists, for example, from the National Art Museum of Ukraine funds [30]. Metadata about these paintings and artists can be collected both on museum portal and on Wikipedia.

CONCLUSIONS

The paper considers the problem of paintings automatic classification using an intelligent decision-making system based on a knowledge graph and Fine-Grained Image Analysis. A solution is proposed in the form of a classifier based on convolutional neural networks with attention model, operating in a multitasking mode.

The architecture of system that performs visual features automatic detection and analysis of Fine-Grained features from picture image, provenance vector formation and picture identification by author, style, genre and time of creation has been developed.

To organize classifier learning, it is proposed to use the loss function based on the angular mismatch between intranet representations of classification objects.

It is proposed to select data for system training and validation from open access datasets, which contain both images of paintings and metadata with descriptions of provenance. In addition, it is proposed to use resources of Ukrainian museums to update the system in Ukraine.

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Received 06.11.2022

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ПРОБЛЕМА АВТОМАТИЧНОЇ КЛАСИФІКАЦІЇ ЗОБРАЖЕНЬ ЗА ВИКОРИСТАННЯ ІНТЕЛЕКТУАЛЬНОЇ СИСТЕМИ ПРИЙНЯТТЯ РІШЕНЬ НА ОСНОВІ ГРАФА ЗНАНЬ І ТОЧНОГО АНАЛІЗУ ЗОБРАЖЕНЬ / А.А. Мартиненко, А.Д. Тевяшев, Н.Є. Кулішова, Б.І. Мороз

Анотація. Для запобігання незаконному вивезенню картин за кордон проводиться музейна експертиза з використанням різних методів дослідження твору мистецтва, зокрема аналіз історичних, мистецтвознавчих, фінансових та інших відомостей і документів, що підтверджують справжність картин – провенансу. Автоматизація такої експертизи ускладнюється необхідністю враховувати числові значення візуальних ознак, показників якості та словесні описи з провенансу. Розглянуто завдання автоматичної багатозадачної класифікації картин під час музейної експертизи. Запропоновано архітектуру системи, яка перевіряє провенанс, реалізує детальний аналіз (FGIA) візуальних ознак зображення та виконує автоматичну класифікацію картини за авторством, жанром та часом створення. Провенанс міститься у графі знань, для векторизації якого запропоновано використовувати енкодер типу graph2vec з механізмом уваги, а детальний аналіз пропонується виконувати за допомогою пошукових відмітних регіонів (SDR) та навчальних відмітних регіонів (LDR), що виділяються згортковими нейронними мережами. Для навчання класифікатора запропоновано узагальнену функцію втрат, а також набір даних, що включає провенанс та зображення картин європейських та українських художників.

Ключові слова: автоматична багатозадачна класифікація, граф знань, механізм уваги, дрібнодетальний аналіз зображень, музейна експертиза, твори живопису, згорткові нейронні мережі.