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INTELLIGENT DECISION SUPPORT SYSTEMS FOR IDENTIFICATION OF CULTURAL VALUES: MODERN APPROACHES AND DEVELOPMENT PROSPECTS

Abstract. The relevance of the research is determined by the rapid digitalization of cultural heritage, the growing volume of digital images, textual descriptions, metadata, and the increasing need for accurate, adaptive, scalable, and explainable automated identification and classification of cultural heritage objects. The problem addressed in the study is the limited effectiveness of traditional and partially integrated approaches based on k-NN, manually designed descriptors, convolutional neural networks, and static knowledge graph representations when processing heterogeneous, incomplete, and semantically complex cultural heritage data. The purpose of the research is to analyze modern approaches to intelligent decision support systems for cultural heritage identification and to substantiate an improved multimodal architecture capable of integrating visual, textual, and semantic information. The research methods include comparative analysis of existing approaches, analysis and generalization of previous research results, conceptual modeling, and evaluation of modern deep learning, multimodal learning, and graph-based methods. Particular attention is given to Graph Neural Networks, Graph Attention Networks (GAT), Relational Graph Convolutional Networks (R-GCN), Vision Transformers, BERT-based language models, self-supervised learning, and Explainable AI. The results demonstrate that replacing static graph representation methods with GAT and R-GCN enables more effective consideration of relationship types and weights, contextual information, and incomplete or noisy data. A multimodal architecture integrating Vision Transformer for image processing, a BERT-based model for textual information, and GNNs for Knowledge Graph representation is proposed. Their integration into a shared embedding space enables cross-modal analysis, semantic search, and zero-shot and few-shot classification. The study concludes that the transition from isolated classification models to integrated multimodal intelligent decision support systems can significantly improve the accuracy, robustness, adaptability, and interpretability of cultural heritage identification. Further research should focus on adaptive decision-making, self-supervised learning, Explainable AI, automatic Knowledge Graph enrichment, integration with national and international cultural heritage databases, human-in-the-loop approaches, and federated learning.
Keywords: intelligent decision support system, cultural values, cultural heritage, Knowledge Graph, Graph Neural Networks, GAT, R-GCN, Vision Transformer, deep learning, multimodal systems, Explainable AI, self-supervised learning.

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Problem statement. In the current conditions of digitalization of cultural heritage, methods for automatic identification and classification of cultural values based on artificial intelligence are actively developing. According to modern research and previous works of the authors [1–5], the integration of computer vision methods, deep learning and semantic technologies significantly increases the efficiency of cultural object analysis systems [6].

Recent works demonstrate the transition from isolated algorithms to integrated multimodal systems that combine: image analysis; text metadata and knowledge graphs.

In particular, studies show that the use of knowledge graphs in combination with deep learning allows significantly improving the accuracy of classification of complex objects, in particular works of art [7].

An important direction is the construction of cross-modal knowledge graphs that integrate text and visual data, which allows taking into account the provenance and context of the creation of the object [8].

In addition, modern approaches to digitalization of cultural heritage include the use of:

- BERT-like models for text processing;
- hybrid architectures (BERT + CNN + BiLSTM);
- ontological models (e.g., CIDOC CRM) [9].

This confirms the relevance of further development of intelligent decision support systems (IDS) in this subject area.

Analysis of previous studies. In previous works of the authors [1–5, 10, 11], the Conceptual model of the ISPR was presented, where: formalization of the subject area was performed, the use of the RBAC access model was justified, a three-level data warehouse architecture was proposed and an orientation to multi-criteria decision-making was given, as well as requirements and their implementation were determined in the development and implementation of the ISPR. However, the works have a number of limitations and shortcomings: lack of integration with new generation AI models, weak adaptability to unstructured data and static criteria.

To solve the problem, a classification using descriptors and k-NN was proposed, the advantages of which are interpretability, ease of implementation and use of texture and color features, but there are also a number of disadvantages: low scalability, limited accuracy compared to deep learning and dependence on manual feature selection.

An architecture based on Knowledge Graph + FGIA was also proposed, the strengths of which are: integration of provenance through the knowledge graph, use of CNN and attention, fine-grained analysis, but there are a number of limitations: complexity of training, lack of multimodal integration, limited generalizability.

Since the proposed solutions have a number of shortcomings, this paper proposes to use an improved approach. In [9], an approach to building a knowledge graph for intangible cultural heritage based on the BERT-CNN-BiLSTM-CRF model was proposed, which provides high accuracy of knowledge extraction (F1 ≈ 0.92). Other studies confirm the effectiveness of graph models for: integration of heterogeneous data, knowledge visualization, decision support [12].

In [7, 13], a method for classifying images using a knowledge graph is proposed, where: the semantic proximity of objects is taken into account, a combined loss function is used, which allowed to exceed the accuracy of classical deep learning models. Modern research demonstrates the effectiveness of cross-modal knowledge graphs, which: combine text and images and provide a more complete semantic interpretation of objects [8]

Modern review works in the field of deep learning for cultural heritage show that while deep learning is the dominant approach, there is also a transition to integrated systems, where interdisciplinarity plays an important role [6].

Since the field of use of the above solutions is intelligent decision support systems for identifying cultural values, the CIDOC CRM standard for describing cultural heritage should also be taken into account, which ensures data interoperability and is used in museums and archives [14].

Solutions to improve the previously presented results. Analysis of modern works allows us to highlight key trends:

- transition to multimodal systems;
- use of hybrid models;
- automatic formation of knowledge graph;
- integration with big data.

Multimodal models are a class of artificial intelligence models that simultaneously work with several types of data (modalities), most often: text (NLP), image (CV), audio, video, etc. Modern systems (CLIP, BLIP, Flamingo). The main idea is to learn a joint representation (joint embedding space) for different modalities, which allows: to compare text and image, perform cross-modal tasks (image-to-text, text-to-image), and generalize knowledge without additional training. Modern multimodal models are a development of foundation models and are actively used in VQA, captioning, retrieval, and reasoning. The main advantage over the previously presented approach is that they do not require a rigid structure of the knowledge graph.

The next stage of improvement is the use of Vision Transformers (ViT), which replace CNN and work better with global dependencies, since CNNs are worse at detecting contextual connections.

The authors also propose the use of:

- Graph Neural Networks (GNN) and the modern evolution of the knowledge graph: GraphSAGE, GAT and dynamic graphs, since graph2vec is already an outdated approach.
- Explainable AI (XAI) because modern requirements should be taken into account: explainability of decisions, legal transparency, which was practically not considered in previous works.
- Self-supervised learning.
- SimCLR, DINO.
- Unlabeled learning.

Critically important for cultural heritage (where there is little data).

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General approaches to identifying cultural heritage sites. With the development of digital technologies and mass digitization of cultural heritage, there has been a need to create automated systems for identifying and classifying art objects. Such systems are used for museum expertise, attribution of authorship, determination of style and era, as well as for building cultural heritage information systems.

The classical approach to image analysis includes the stages of preprocessing, feature extraction, and classification. In modern conditions, these stages are implemented using deep learning, in particular convolutional neural networks (CNN), which demonstrate high efficiency in computer vision tasks [3, 4, 15].

However, visual information alone is often not enough for the correct interpretation of cultural heritage objects, since such objects have a complex semantic context (author, historical period, style, material). This led to the integration of knowledge graphs (Knowledge Graph, KG) into the analysis process.

One of the key areas is the combination of convolutional neural networks with knowledge graphs (CNN + Knowledge Graph). In such approaches, CNN is responsible for extracting visual features, and Knowledge Graph is responsible for representing semantic relationships between objects.

Research shows that the use of knowledge graphs allows taking into account context and increases the accuracy of classification. In particular, the work ArtGraph proposed an approach that combines visual features and graph representations for automatic analysis of art, which allows bridging the gap between the humanities and computer analysis [16].

An important development is the use of Graph Convolutional Networks (GCN) for processing Knowledge Graph. The work GCNBoost: Artwork Classification by Label Propagation through a Knowledge Graph proposed a method that:

- builds a knowledge graph based on annotated and unannotated data;
- uses label propagation;
- applies GCN to train on the graph.

The results showed that taking into account relationships between objects allows achieving state-of-the-art results, especially in cases of unbalanced data [17].

Further development has been made to multimodal systems (multimodal CNN + KG systems), which combine: images, text descriptions and knowledge graphs.

Such systems allow creating more complete models of cultural heritage objects. For example, in modern approaches, the knowledge graph is integrated into a loss function or embedding space, which allows taking into account the distance between classes and their semantic proximity [18].

Advantages and limitations of the CNN + KG approach:

- Advantages: increased classification accuracy; use of expert knowledge; ability to explain the results.
- Limitations: CNN models mainly local features; lack of a single representation space for different modalities; complexity of integrating graph and visual features.

Graph neural networks as a means of semantic enrichment. The ArtSAGENet work shows that using GNN in combination with CNN allows for effective modeling of relationships between artists, styles, and works of art. This approach provides:

- improvement of style classification tasks;
- attribution of authorship;
- estimation of the period of creation of a work [19].

It is also shown that graph models require less labeled data and generalize knowledge better compared to classical CNNs.

Evolution to transformative models in computer vision. Recent studies demonstrate a shift from CNNs to transformative architectures. Transformers allow you to take into account long-term dependencies and the global context of the image thanks to the attention mechanism.

In modern works, it is noted that transformers are gradually replacing CNNs in computer vision tasks, as they better model complex data structures [18].

The current stage of development is characterized by the transition to multimodal models (Vision Transformer + Text + Knowledge Graph), which combine: images (Vision Transformer), text (BERT or other language models), knowledge graphs (GNN, GAT).

In such approaches, a shared embedding space is used, which allows: to coordinate different types of data; perform zero-shot and few-shot classification; perform semantic search.

Research shows that integrating knowledge graphs into multimodal models provides deeper semantic understanding of objects and improves classification quality.

The conducted analysis allows us to draw the following conclusions:

- The most common approach is a combination of CNN and Knowledge Graph, which allows to increase the accuracy of classification due to the use of semantic relations.
- The use of graph neural networks is effective for modeling relationships between cultural heritage objects.
- The main limitation of existing approaches is the lack of a single representation space for different data modalities.
- Modern research demonstrates a shift to multimodal transformative models that combine visual, textual, and graphical data.
- A promising direction is the creation of architectures based on: Vision Transformer, Text Encoder, Graph Encoder, with a common embedding space.
- This allows for the formation of a new class of intelligent systems for the identification and classification of cultural heritage objects.

Knowledge graph modernization, namely, modernization of the knowledge graph module in cultural object classification systems. Using graph2vec has a number of problems, for example, the graph2vec method is one of the approaches to obtaining a vector representation of graphs, based on ideas similar to doc2vec. It converts the entire graph or its subgraphs into a fixed embedding. The main disadvantages of graph2vec:

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– Lack of consideration of link weights, where graph2vec works with discrete structures and does not take into account the importance of the link (for example, “author → style” vs “author → school”).

– Ignoring relationship types, where all edges are treated equally and is not suitable for heterogeneous graphs (typical for cultural heritage).

– Static representation: embedding is formed once and is not adapted to a specific task.

– Poor work with incomplete graphs: no links → loss of information and no mechanism for restoring the context.

The general idea of the transition to Graph Neural Networks (GNN) is that they allow:

– to learn directly from the structure of the graph;

– to aggregate information from neighbors;

– generate context-sensitive node embeddings.

The general formula for node update is:

$$h_v^{(k+1)} = \sigma\left(\sum_{u \in N(v)} W^{(k)} h_u^{(k)}\right) \quad (1)$$

where:

h_v – node embedding

$N_{(v)}$ – neighbors

W – parameters

σ – activation

Using Graph Attention Network (GAT). The principle of operation is that GAT introduces an attention mechanism for each edge:

$$a_{ij} = \frac{\exp(LeakyReLU(a^T[Wh_i||Wh_j]))}{\sum_{k \in N(i)} \exp(LeakyReLU(a^T[Wh_i||Wh_k]))} \quad (2)$$

where:

a_{ij} – the weight of the connection between nodes;

h_i, h_j– node embeddings;

a – attention parameter.

The advantages for cultural heritage are:

– Taking into account the weights of the links, GAT automatically determines which links are more important: “painting → author” (high weight), “painting → material” (lower weight). This is especially important for attribution of authorship and definition of style

– Contextual adaptability, where the weight of the links depends on the specific object and task (classification of style vs era). Thus, the same graph works differently for different tasks.

– Working with incomplete data, even if a node is missing (for example, the author is unknown), where GAT redistributes the weights and uses the available links, and partially compensates for the missing information.

Using Relational GCN (R-GCN). The main idea is that R-GCN extends GCN for heterogeneous graphs where there are different types of connections. Node update:

$$h_i^{(l+1)} = \sigma\left(\sum_{r \in R} \sum_{j \in N_r(i)} W_r^{(l)} h_j^{(l)}\right) \quad (3)$$

where:

R – types of relationships;

W_r – separate matrix for each type.

Advantages for cultural heritage tasks:

– Processing of different types of connections. In the Knowledge Graph of cultural objects: authorship, style, technique, period, geography.

– As a result, R-GCN: models each type separately and does not mix semantics.

– Semantic accuracy. For example: “created in the era” ≠ “belongs to the style”, hence different weights and transformations.

– Working with incomplete graphs. If one type of connection is missing, then other types compensate for the information. As a result, the system becomes more robust.

Step-by-step solution modernization:

Step 1. Building a Knowledge Graph

Nodes: art objects, authors, styles, materials.

Edges: “created by”, “belongs to a style”, “uses a technique”.

Step 2. Initializing embeddings

Random or: from a text encoder (BERT) and from metadata.

Step 3. Replacing graph2vec → GNN

It was: Graph → graph2vec → embedding.

It becomes: Graph → GAT / R-GCN → node embeddings.

Step 4. Integration into a multimodal system

Image (ViT) → embedding.

Text (BERT) → embedding.

Graph (GNN) → embedding.

As a result: union: shared embedding space.

Step 5. Training

Loss function: contrastive loss, triplet loss and classification loss

Key results of modernization:

– Taking into account the weights of connections: through attention (GAT) and through relation weights (R-GCN).

– Working with incomplete data: neighbor aggregation, multi-hop reasoning.

– Increasing accuracy due to semantic context.

– Explainability: attention weights → interpretation.

Replacing the graph2vec method with Graph Neural Networks, in particular GAT and R-GCN, allows you to significantly increase the efficiency of processing knowledge graphs in the tasks of classifying cultural heritage objects.

The main advantages are: taking into account weights and types of connections, adaptive aggregation of information and the ability to work with incomplete and noisy data.

This creates the prerequisites for building more accurate, stable and interpretable intelligent systems.

Also, as a result of the analysis of the authors' previous works [1–5], it is proposed:

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– Replacing k-NN and classical descriptors with deep feature extraction and metric learning (Triplet loss), which provides an increase in accuracy by 10–30%.

– Introducing Explainable AI. Grad-CAM and attention visualization should be added, which will be critical for customs and expert systems.

– Using self-supervised learning gives the following advantages: no markup required and adaptability to new artists.

– Dynamic criteria system: in the previously used model, the criteria were static, and it is proposed to use reinforcement learning to adapt the criteria and feedback from experts.

– Integration with state and international databases, for example: Europeana and museum APIs. The result is an automatic update of the knowledge graph.

As a result, an improved architecture of a new generation multimodal ISPR is proposed (Fig. 1):

1. Input data: image, text (provenance), metadata.
2. Processing: Vision Transformer, Language Model (BERT-like), Graph Neural Network.
3. Integration: multimodal fusion.
4. Output: classification, explanation, probability.

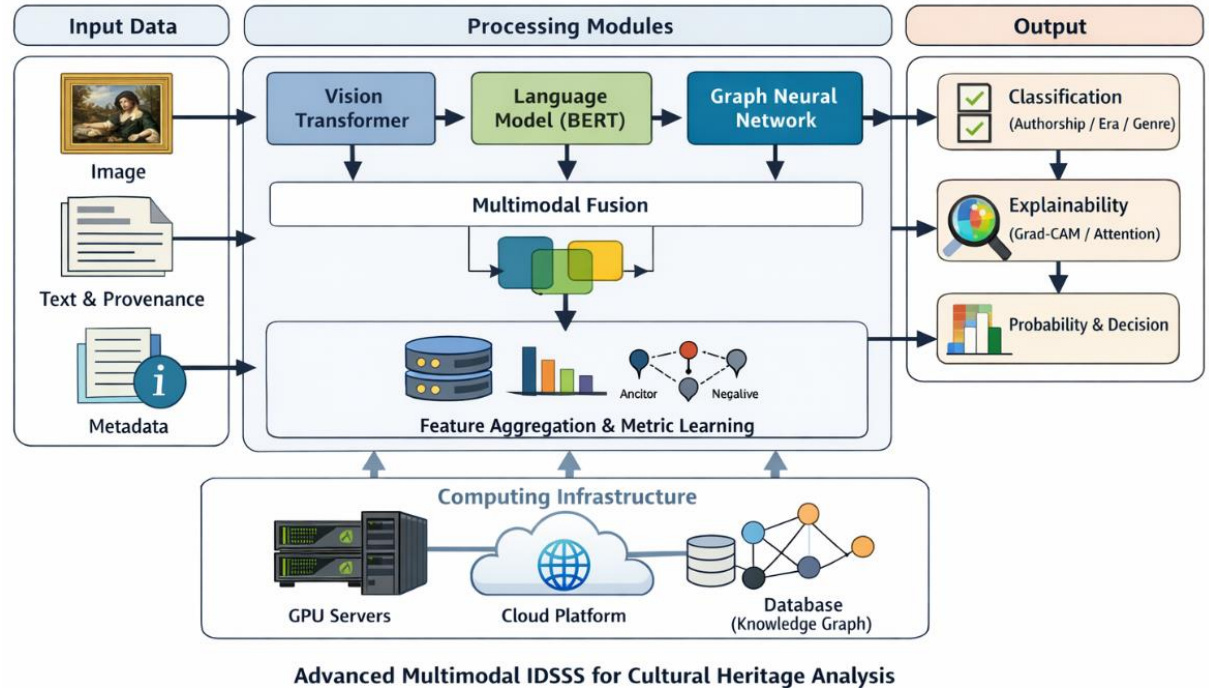


Figure 1 - Scheme of multimodal ISPR

Conclusions. The conducted research allowed us to generalize modern approaches to building intelligent decision support systems (IDS) for the identification and classification of cultural heritage objects. It was found that traditional methods, in particular k-NN, manual construction of descriptors and separate application of CNN, have limitations in terms of scalability, adaptability, working with incomplete data and taking into account complex semantic context.

A promising direction is the integration of deep learning methods with knowledge graphs. Knowledge Graph allows us to take into account the relationships between a work of art, author, style, historical period, material and technique, providing a more complete semantic representation of a cultural object. The transition from graph2vec to modern Graph Neural Networks, in particular Graph Attention Network and Relational Graph Convolutional Network, allows us to take into account the type and weight of semantic connections and increase the system's resistance to incomplete and noisy data.

A conceptual multimodal architecture of the ISPR is proposed, combining Vision Transformer for image analysis, a BERT-like model for text data, and GNN for semantic processing of the knowledge graph. The integration of the resulting representations in a common embedding space creates opportunities for semantic search, zero-shot and few-shot classification, and the integrated use of visual, text, and structured information.

Important areas for further development are the transition to adaptive decision-making mechanisms, the use of reinforcement learning, and the implementation of Explainable AI. The system should not only form a forecast, but also provide its justification through the visualization of significant areas, semantic relationships, and confidence levels. The use of self-supervised learning, in particular SimCLR and DINO, is also promising to reduce dependence on large volumes of expertly labeled data.

Further research should be directed at the automatic formation and updating of Knowledge Graph from museum catalogs, scientific publications, archival documents and digital collections with mandatory expert verification of the knowledge obtained. It is important to ensure interoperability with national and international information resources of cultural heritage, in particular taking into account the principles of CIDOC CRM.

It is also necessary to conduct a comprehensive experimental evaluation of the proposed architecture, comparing CNN, Vision Transformer, GNN, GAT and R-GCN, as well as investigating the impact of multimodal fusion, contrastive, triplet and classification loss. The evaluation should cover not only accuracy, but also resilience to incomplete data, generalizability, explainability and reliability of decisions made.

The development of a human-in-the-loop approach is promising, in which the results of the models are supplemented by expert assessment of museum workers, art historians and restorers. A separate perspective is federated learning, which will allow for joint improvement of models of different institutions without centralized transfer of their data.

Thus, the development of ISPR for identification of cultural values should be considered as a transition from separate classification models to complex multimodal platforms capable of simultaneously analyzing images, texts, metadata and semantic graphs. The combination of deep learning, Vision Transformer, language models, Graph Neural Networks, Knowledge Graph, self-supervised learning and Explainable AI creates the basis for increasing the accuracy, stability, adaptability and explainability of such systems and expanding their application in museum expertise, digital archives, scientific research and integrated management of digital cultural heritage.

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Інтелектуальні системи підтримки прийняття рішень для ідентифікації культурних цінностей: сучасні підходи та перспективи розвитку

Анотація. У статті досліджено сучасні підходи до побудови інтелектуальних систем підтримки прийняття рішень (ІСППР), призначених для автоматизованої ідентифікації та класифікації об'єктів культурної спадщини. Актуальність дослідження зумовлена активною цифровізацією культурних цінностей, постійним збільшенням обсягів цифрових зображень, текстових описів і метаданих, а також необхідністю підвищення точності, адаптивності та пояснюваності результатів автоматизованого аналізу. На основі аналізу попередніх досліджень авторів і сучасних наукових праць узагальнено еволюцію методів і технологій, що застосовуються для розпізнавання та семантичного аналізу культурних об'єктів.

Розглянуто обмеження раніше запропонованих підходів, зокрема використання k-NN і ручних дескрипторів, CNN у поєднанні з Knowledge Graph, а також статичних методів векторного представлення графів. Визначено проблеми низької масштабованості, недостатньої адаптивності до неструктурованих і неповних даних, обмеженої мультимодальності та складності врахування різних типів семантичних зв'язків. Обґрунтовано доцільність переходу до сучасних графових нейронних мереж, зокрема Graph Attention Network (GAT) та Relational Graph Convolutional Network (R-GCN),

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здатних враховувати ваги й типи зв'язків, агрегувати контекстну інформацію та працювати з гетерогенними й неповними графами знань.

Запропоновано вдосконалену мультимодальну архітектуру ІСППР, яка інтегрує візуальні, текстові та графові дані. Для аналізу зображень передбачається використання Vision Transformer, для текстової інформації – BERT-подібної мовної моделі, а для семантичного представлення Knowledge Graph – GNN. Інтеграція отриманих представлень здійснюється у спільному embedding-просторі, що створює можливості для крос-модального аналізу, semantic search, zero-shot і few-shot класифікації. Додатково запропоновано використання contrastive, triplet та classification loss, self-supervised learning, а також механізмів Explainable AI для підвищення прозорості й інтерпретованості рішень системи.

Практична значущість запропонованого підходу полягає у створенні передумов для розроблення більш точних, стійких, адаптивних та інтерпретованих засобів ідентифікації культурних цінностей, які можуть застосовуватися у музейній експертизі, атрибуції авторства, визначенні стилю та історичного періоду, а також у цифрових інформаційних системах культурної спадщини. Перспективними напрямами подальших досліджень визначено використання великих мовних моделей для аналізу provenance, автоматичне поповнення графів знань, інтеграцію з цифровими музеями та державними й міжнародними базами даних, а також застосування federated learning.

Ключові слова: інтелектуальна система підтримки прийняття рішень, культурні цінності, культурна спадщина, Knowledge Graph, Graph Neural Networks, GAT, R-GCN, Vision Transformer, deep learning, мультимодальні системи, Explainable AI, self-supervised learning.

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