ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume X-M-2-2025
30th CIPA Symposium "Heritage Conservation from Bits:
From Digital Documentation to Data-driven Heritage Conservation", 25–29 August 2025, Seoul, Republic of Korea

Development of an Artificial Intelligence-based Platform for the Analysis and Utilization of Cultural Heritage Data

Seohyun Baek[1], Hyerin Hwang[1], Chan-Woo Park[1], Hee-Kwon Kim[1], Jae-Ho Lee[1]*

[1] Content Research Division, Electronics and Telecommunications Research Institute, Daejeon, Korea
– (b_seohy, hyerin, gamer, hkkim79, jhlee3)@etri.re.kr (*corresponding author)

Keywords: Platform, Artificial Intelligence, Cultural Heritage Data, Data Analysis, Management, Museum.

Abstract

This research presents the development of an AI-powered digital cultural heritage platform designed to address the growing need for efficient management, analysis, and utilization of traditional cultural assets in the era of rapid digital transformation. The platform integrates a digital archive, data-driven AI analysis modules, generative AI techniques for content enrichment, and an operational environment for demonstration and deployment. It supports the stable storage and intelligent processing of diverse cultural heritage data. A notable feature is the implementation of an AI-based relational analysis model that captures the complex metadata and structural relationships inherent in cultural heritage objects, enabling the automatic identification and visualization of meaningful semantic connections. The platform also incorporates dedicated viewers—such as RTI, Giga Pixel, GLB, and NXG—offering intuitive access to ultra-high-resolution and 3D representations of cultural objects. This multifaceted system supports a wide range of applications in education, academic research, and exhibition contexts, demonstrating its versatility and strong potential for practical implementation across public and scholarly domains.

1. Introduction

The advancement of digital technologies, the increase in storage capacity, the sophistication of communication technologies, and the development of high-performance computing have created a growing tendency to demand more practical, accurate, and information-rich content (Lee et al., 2024a). These technological changes have led to cultural heritage utilizing digital technology gradually gaining attention since the spread of computers in the mid-1980s, and countries with long histories, including those in Europe, are showing increased interest in the preservation of their cultural heritage and the revitalization of cultural heritage industries (Park, 2024). Many countries around the world are exploring various methods to allow more people to share and enjoy the cultural heritage they possess, and related research is also being actively conducted. This trend has naturally led to the generation of vast amounts of digital data across various fields, and the amount of data is expected to increase exponentially in the future. Digital transformation is also bringing new changes to museum operations. Museums have come to generate enormous amounts of digital data, and consequently, the necessity of developing digital heritage sharing platforms for the continued utilization and preservation of traditional cultural heritage content is increasingly being highlighted (Dong et al., 2014, Lim et al., 2017, Nam et al., 2019, Dai et al., 2019, Teichmann et al., 2019, Lee et al., 2024b).

Digital cultural heritage refers to activities involving research, preservation, exhibition, management, documentation, and dissemination based on the fusion of cultural heritage expertise with advanced ICT and content technologies (Park et al., 2024). Recently, it has evolved beyond simple preservation and management purposes to produce new forms of content and provide information in various formats (Kim et al., 2024). However, merely digitizing data in various formats does not automatically render that information useful (Lee et al., 2024a). To secure practically applicable digital information, the collection and preprocessing of data, design of systems suitable for data characteristics, and input of additional information must be integrated comprehensively. To prepare for the future-oriented digital transformation of museum cultural heritage data, it is essential to define appropriate structures and standards for the data, and existing collected data should also be reorganized according to these structures and standards (Lee et al., 2024a). This process includes not only the creation of new data but also the conversion and reorganization of existing data, requiring significant time, effort, and budget. Therefore, for an efficient approach to digital cultural heritage data generation and conversion, technological development such as artificial intelligence and big data must be pursued concurrently.

The National Museum of Korea began building digital data in the early 2000s; however, it was initially limited to archiving purposes (Park et al., 2024). Recently, research on how to effectively utilize the accumulated data has gradually intensified. The museum is developing immersive content based on 3D assets created using precision scanners and high-resolution cameras for major cultural heritage items, and actively exploring ways to repurpose existing data by integrating artificial intelligence technologies (Park et al., 2024). As the digital transformation of cultural heritage accelerates, the importance of technology development for systematic management and sophisticated utilization of cultural heritage content is increasingly emphasized. Effective digital cultural heritage management and utilization require the prior acquisition of high-quality digital content with precision and reliability, as well as the establishment of data fabric-based archive technology capable of stably storing and operating vast amounts of data. Additionally, the development of precise analysis and efficient search technologies for cultural heritage data utilizing artificial intelligence, along with the development of public service-oriented integrated platform technologies that can be utilized by various institutions and users, is essential.

This research aims to develop a digital heritage platform that encompasses these key elements. The objective is to pioneer the standardization of cultural heritage digital data to support multi-purpose utilization and to develop an artificial intelligence-based digital heritage platform that can be used for specialized traditional cultural heritage services and the creation of globally

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
https://doi.org/10.5194/isprs-annals-X-M-2-2025-39-2025

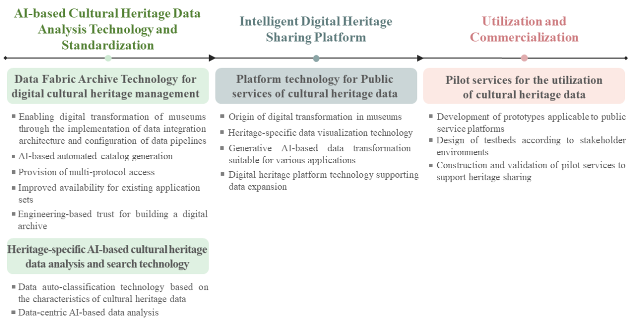

Figure 1. Research and development items of intelligent digital heritage sharing platform (Lee et al., 2024b).

competitive content. To achieve this, we seek to establish standards for the generation, transformation, processing, analysis, and visualization of digital heritage data and to research core technologies for a traditional cultural heritage digital heritage platform that can be expanded for various uses such as metaverse and digital twin applications.

This research focuses on developing a digital heritage platform centered around four key technologies. First, we will establish an engineering trust-based digital archive that constructs a data pipeline including a data integration architecture for efficient management of vast cultural heritage data, provides AI-based automatic catalog generation and multi-protocol access, and ensures availability for existing application sets. Second, we will perform data analysis that supports automatic classification based on cultural heritage data characteristics and enables users to easily access cultural heritage data using Data-Centric AI approaches. Third, we will develop platform technology that integrates Generative AI-based data transformation techniques with cultural heritage-specific visualization technologies to secure content extensibility applicable to various public services and creative fields for practical utilization of cultural heritage content. Finally, we will design prototype demonstration services to apply the developed technologies to actual demand institutions' environments and verify the validity of the technology by implementing demonstration services across multiple museums.

The proposed approach has significant academic and technological implications in that it offers an integrated platform that combines artificial intelligence technology with digital archiving technology for the preservation and utilization of cultural heritage data. In particular, cultural heritage data contains unique meta-information that presents limitations when processed with conventional data processing technologies. By establishing standardized data structures and processing technologies that reflect these specificities, our work presents an advanced digital cultural heritage management system that goes beyond the existing fragmentary digitization level. Additionally, by applying generative artificial intelligence and data fabric technology to cultural heritage, this initiative lays the foundation for content utilization and contributes to securing independent competitiveness for domestic digital heritage technology.

2. Related work

2.1 Previous platform

The Google Arts & Culture is a global digital cultural heritage platform operated by Google that, in collaboration with the Google Cultural Institute, digitizes heritage content from museums and art galleries worldwide as high-resolution images and provides them online. Particularly utilizing 'Art Camera' technology, it implements gigapixel-level ultra-high-definition images and provides a web-based catalog that allows users to freely zoom in on image details while viewing accompanying explanatory notes. It also realizes immersive digital exhibitions through Google Street View, VR technology (Google Cardboard), machine learning-based content curation functions, and AI-based image analysis technologies, with participation from over 600 global museums and art galleries. A notable example is 'The Museum of the World,' co-produced with the British Museum, which provides an interactive virtual exhibition environment where exhibits can be sorted chronologically or thematically and explored visually.

Europeana is a public-centered integrated digital cultural heritage platform established under the leadership of the European Union (EU), with participation from over 2,200 institutions across 33 European countries including France, Germany, and Sweden. It standardizes and provides cultural heritage information in various formats such as text, images, video, audio, and 3D data based on metadata, and as of January 2023, it possesses over 50 million digital objects, including more than 30 million images and 20 million text data. Europeana enables interconnectivity and contextual information complementation between institutions through its proprietary technology, EDM (Europeana Data Model), and RDF-based metadata model, and features a digital repository and archiving intensive structure encompassing European civilization.

e-Museum is a national-level integrated digital cultural heritage platform operated by the National Museum of Korea. It aggregates and provides collection information from public, national, and private museums and art galleries across the country. With over 1.8 million records and more than 1.9 million high-resolution images, the platform facilitates easy access to cultural heritage resources for the general public, as well as for researchers and educators. While it offers participatory features such as user-curated content, key limitations include regional bias in content diversity, a lack of intuitive user interface design, and limited community-based interactive functions, all of which have been identified as areas for improvement.

Although all three platforms—Google Arts & Culture, Europeana, and e-Museum—share a common goal of collecting, preserving, and utilizing digital cultural heritage, they differ in operational frameworks and implementation strategies. Google Arts & Culture emphasizes a technology-driven, immersive user experience, whereas Europeana focuses on public-centered metadata integration and standardization, with a strong emphasis on academic utility. e-Museum contributes by establishing a nationally integrated database and enhancing public accessibility; however, it still needs to strengthen its technological scalability and interactivity to evolve into a globally competitive platform.

2.2 Technologies

The platform proposed in this research integrates various artificial intelligence and database-based technologies to structurally store, efficiently retrieve, and visually restore and recommend cultural heritage data. First, a Neo4j-based graph database (Neo4j, n.d.) was constructed to represent the relationships among cultural heritage items and their metadata linkage structure. Neo4j is a graph database management system that provides tools for graph data storage, computation, data management, and analysis, enabling efficient development and utilization of graph-based data applications. The semantic graph consists of nodes representing various metadata elements—such as exhibition type, holding institution, thematic classification, type, and digital file format—centered around each cultural heritage object. Edges are used to define the relationships between these elements. This structure allows users to explore not only individual cultural assets but also structural and semantic connections among them, while also supporting visual navigation through linked digital files.

To systematically manage cultural heritage data, an administrator-specific database management system is provided. Through this system, users can upload files related to cultural heritage and input or edit a wide range of metadata, including unique identifiers (ID), classification items (era, material, lifestyle, museum, collection number, dimensions, etc.), image files, and 3D models. Uploaded files can be reviewed by status and are integrated with the system's semantic graph, search, and recommendation modules. This enables a standardized and consistent metadata management environment that supports multiple file formats (JPEG, PNG, OBJ, GLB, etc.).

The image-based similarity analysis and recommendation functions for cultural heritage are implemented via the Gradio interface (Abid et al., 2019). When a user uploads an image, it is vectorized using a pre-trained image embedding model from CLIP (Radford et al., 2021), and visually similar heritage items are displayed in a two-dimensional scatter plot within the overall embedding space. For a selected item, a metadata-based multi-label classification model is applied to predict attributes such as material, era, and lifestyle. Based on these predictions, the system automatically recommends related heritage items for each attribute (Hwang et al., 2025). This feature is also extended to the detail page of each cultural heritage item within the platform, where similar items are automatically recommended when users view individual item information.

Additionally, an image inpainting model (Yu et al., 2019) is adopted to restore images of cultural heritage items that have visual damage, such as stains or blemishes. The system utilizes a deep learning-based inpainting model (Li et al., 2023) specialized for shadow removal to automatically restore damaged regions based on the contextual information of surrounding visual features. This inpainting method enhances the visual quality of damaged cultural heritage images and helps minimize information loss during digital preservation processes. Each of these technologies functions independently but is also interconnected within the platform, providing an integrated workflow that spans data registration, retrieval, similarity-based recommendation, and damage restoration.

3. Development of platform technology for public services

The platform presented here is a digital standard sharing platform that supports the efficient management and utilization of cultural heritage content data. Previously, it was common practice for data to be individually generated and fragmentally managed according to purposes such as exhibition, education, and preservation. This research aims to overcome these limitations and proposes an integrated management system that can enhance the scalability and flexibility of cultural heritage data.

3.1 Strategies for feature analysis and standardization in systematic management of cultural heritage data

Since the early 2000s, comprehensive research on digital cultural heritage data management has been conducted in Europe through the Europeana group (Park et al., 2024). However, existing management systems and digital data structures present numerous challenges in accommodating the diverse digital data currently being produced. The most significant issues identified include data fragmentation, data integrity, limitations of RDF schemas, and the complexity of digital cultural heritage data. Furthermore, applying the structures established by leading institutions in Europe and the United States to the Korean context presents additional difficulties. To enable systematic generation and utilization of cultural heritage digital data, this research conducted a comprehensive analysis of data structures, attributes, and management methodologies to establish a standardization framework. In particular, we developed detailed criteria for categorizing data attributes including characteristics, categories, and sizes to ensure sustainable management and value expansion of digital cultural heritage data. This represents the first attempt at standardizing cultural heritage digital data creation in Korea. By collecting representative types of both structured and unstructured data held by museums, we expanded the breadth and depth of the data, thereby securing foundational materials for establishing an ontology-based data structure.

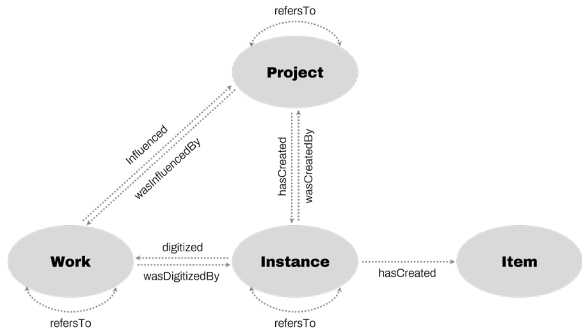

Figure 2. Data relationship structure diagram (Kim et al., 2024).

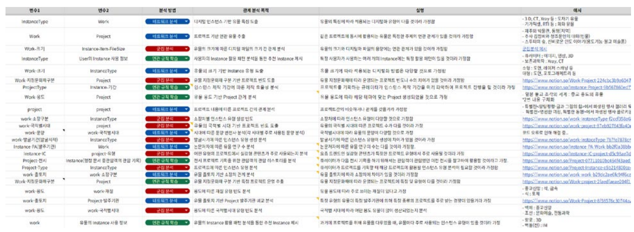

Figure 3. List of data combinations for cross-correlation.

Reflecting the characteristics of museums, we systematized a data layer structure consisting of work, project, instance, and item, clearly defining the roles and relationships between each layer. Based on this structure, we analyzed the workflow and data generation methods of museums and further refined the types of projects and instances. Particularly, by establishing data reusability and interoperability as core values and defining relationships between minimum unit data, we enabled data sharing and utilization among diverse users (public, industry, academia). We derived practical data structure improvements by investigating various cultural heritage systems including the National Museum of Korea website, e-Museum, Digital Asset Management System (DAMS), Cultural Heritage Standard Management System, Oegyujanggak Uigwe Comprehensive DB, and Japanese Colonial Period Data Disclosure System, and analyzing actual data. Additionally, we structured relationships between data layers using CIDOC-CRM and secured interoperability and scalability through 1 matching with international standard metadata such as Dublin Core, Schema.org, CARARE, and BIBFRAME 2.0. Limitations of existing metadata were addressed through comparative analysis with international standards, and missing elements were newly defined to enhance the completeness and comprehensiveness of metadata. As a result, this research constructed a total of 12,131 cultural heritage digital data items according to the hierarchical structure. In this process, metadata inputs were organized into rule-based structures using Excel, then implemented in source DBMS form through database design and migration processes. Furthermore, reflecting the requirements of the National Museum of Korea as the demand institution, we designed a pipeline structure compatible with their classification system and metadata specifications. We configured a pipeline framework considering integration with existing systems such as e-Museum and Cultural Heritage Standard Management System, and secured search efficiency and system consistency by coding the cross-reference and relationship structures between data sets.

Each layer in Figure 2 permits cross-referencing and enables sharing of information about reuse and creators. As digital cultural heritage data is utilized in various forms of content such as catalogs, education, books, and experiential activities, the configuration of interrelationships has become critically important. This visualization of interrelationships facilitates efficient data reuse and management. The proposed digital cultural heritage data structure is designed to encompass EDM (Europeana Data Model) to achieve global standardization and leadership. The definitions of the four layers (Work, Project, Instance, Item) can be mapped to EDM's RDF schema and incorporate structures for data integrity and relational connections. This pipeline system functions as an intelligent data management framework that connects data flows flexibly across various sectors including public institutions, industry, and education, rather than confining cultural heritage data within a single institution. Furthermore, as the first case in Korea to systematize a layer-based pipeline for the entire lifecycle management of digital cultural heritage data, it is expected to make substantial contributions to standardization, dissemination, and application in the future. The significance of this research lies in establishing the foundation for a digital cultural heritage management system in Korea while securing expandability that considers international interoperability through these standardization and structuring processes.

3.2 Semantic Graph-Based Visualization of Cultural Heritage Metadata

This visualization technique structures cultural heritage data of various formats into a knowledge graph, providing a knowledge-based interface for exploring integrated forms of digital assets. Figure 4 illustrates a semantic graph visualization method implemented on the cultural heritage platform that embodies this approach. Figure 4(top) presents a semantic network centered on a specific cultural heritage object, the "Gilt-bronze Pensive Bodhisattva," in which the relationships among associated metadata are represented through a node-link structure. The graph is implemented using the Neo4j graph database and includes metadata elements such as institution, exhibition location, thematic category, type, repository, and file format. Each node represents a metadata attribute, while edges denote semantic relationships such as affiliation, association, or transformation. In addition, related heritage objects are visualized in clustered groups within the graph, allowing users to understand thematically related cultural heritage items by cluster. Figure 4(bottom) extends the abstract structure of Figure 4(top) by visualizing the connections between actual digital files—such as 3D scan outputs, texture images, material files, and 3D models—linked to the metadata. Each digital asset is visually distinguished by hierarchical types such as "Item," "Work," and "Instance." This enables users to intuitively explore the connection structure between a cultural heritage object and its associated digital resources, enhancing the understanding of both contextual and functional data structures.

3.3 Structured Metadata Registration and File Management System

For integrating and systematically managing cultural heritage data, a dedicated management interface that enables data input, modification, and tracking is essential. In this research, we developed a database management system for the integrated cultural heritage platform to fulfill these requirements. Figure 5 visually presents the interface of this system which is designed to allow administrators to upload various cultural heritage data register and modify metadata and monitor the processing status of uploaded files in real-time.

This system enables administrators to upload various cultural heritage data, register and modify metadata, and monitor the processing status of uploaded files. Each cultural heritage entry is systematically organized with a unique ID, related documents, and classification attributes, contributing to the consistency and integrity of the data. Administrators can manage and track upload histories and file statuses in real time, thereby

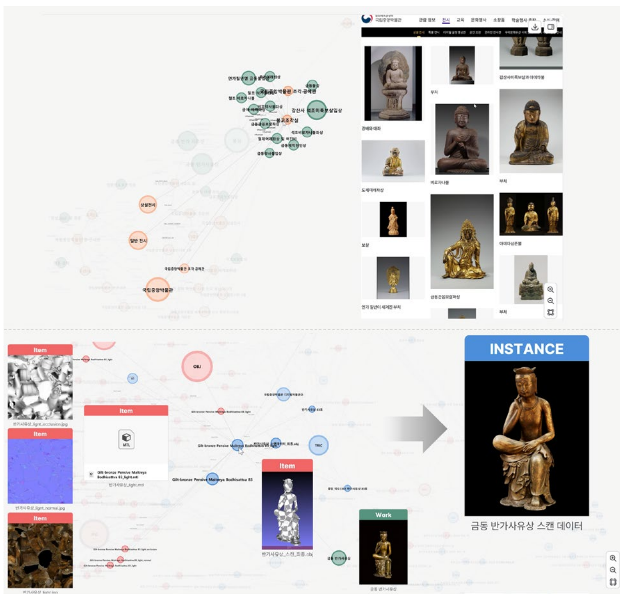

Figure 4. (top) Semantic graph of cultural heritage metadata centered on the "Geum-dong Bangasayusang"; (bottom) Linked digital files visualizing connections between metadata and related content.

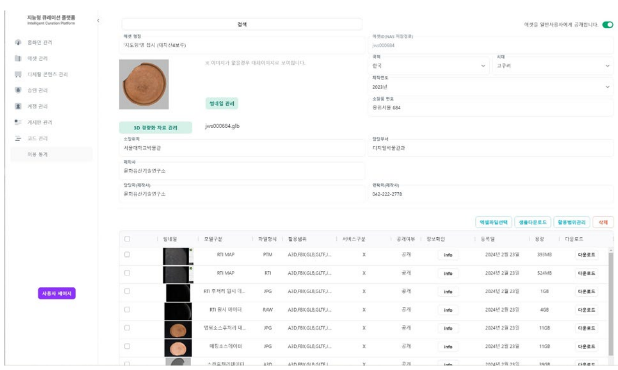

Figure 5. Cultural heritage database management interface for metadata editing and file monitoring.

facilitating efficient integration and digital management of cultural heritage information. This function plays a crucial role within the platform by structuring cultural heritage data and enabling seamless interoperability with the overall system.

3.4 Image-Based Recommendation System for Cultural Heritage Images

3.4.1 System Overview: Cultural heritage data possesses various attributes, including visual characteristics, historical context, and functional purposes. Technologies capable of automatically classifying and recommending such data based on these complex features are emerging as key elements in the digital utilization of cultural heritage. In this study, we developed a system that can analyze the characteristics of a cultural heritage item and recommend similar items based solely on a single image input. Figure 6 presents an example of the image-based cultural heritage recommendation system implemented using Gradio. When a user uploads an input image, the system visualizes visually similar heritage items in a two-dimensional embedding space through a scatterplot, based on an internal similarity analysis model. For this analysis, the system employs CLIP (Contrastive Language–Image Pretraining), which enables multimodal representation learning between images and texts, allowing the system to recommend semantically similar cultural heritage items. For each selected item, metadata-based analysis is conducted to estimate the likelihood of key attributes such as material, historical period, and lifestyle. Based on these predictions, the system recommends representative related heritage items for each attribute.

Hwang et al. (2025) augmented visual data using generative models and predicted cultural heritage attributes—such as material, age, and lifestyle—through multi-label classification. In contrast, the present study directly analyzes the semantic similarity of actual input images within the CLIP embedding space to recommend relevant heritage items.

Once an image is input into the CLIP model, which has been fine-tuned on cultural heritage data, it is mapped into the multimodal embedding space. The system then calculates cosine similarity between the input and existing cultural heritage embeddings to identify semantically similar items. For the top-ranked similar items, the system performs metadata analysis and recommends representative heritage items for each attribute category such as material, age, and lifestyle.

The proposed AI-based approach is also integrated into the cultural heritage detail page of the platform. As shown in Figure 7, when a user views information about a specific heritage item, the system automatically recommends related items based on visual or semantic similarity.

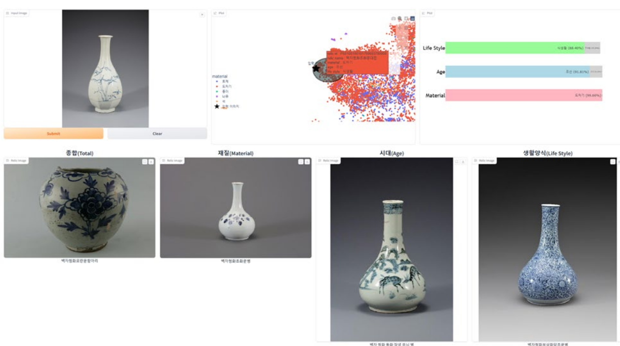

Figure 6. Image-based recommendation interface visualizing similar cultural heritage items and attribute predictions.

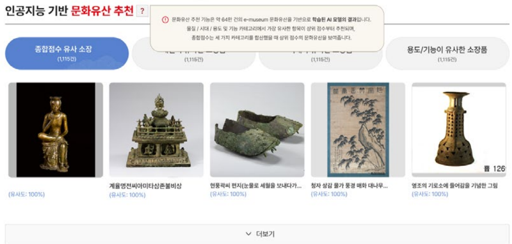

Figure 7. Application of the AI-based method within the cultural heritage detail page of the platform.

3.4.2 Experimental Setup and Evaluation: A summary of the system configuration and evaluation results is provided in Table 1. Approximately 83,000 cultural heritage images were utilized in this study. These were selected by filtering from an original set of around 2.5 million images to retain only those with all three key attributes—material, historical period, and lifestyle—explicitly annotated. A CLIP-based embedding model was trained on this filtered dataset for use in the recommendation system. For quantitative evaluation, the system was tested by inputting a single image, which then automatically recommended semantically similar cultural heritage items and predicted key attributes (material, age, lifestyle), displaying representative items for each attribute category. Table 2 presents the quantitative evaluation results of semantic analysis and metadata processing components within the intelligent cultural heritage platform. The evaluated functions include semantic search accuracy, material classification performance, and the number of digital heritage items added to the metadata database. As shown in Figure 6, when a ceramic bottle image was input, the system predicted the material as "ceramic" (99.66%), the age as "Joseon" (91.81%), and the lifestyle category as "culinary" (88.40%), followed by recommendations accordingly. Semantic search accuracy is discussed in Section 3.2, the addition of metadata-driven digital heritage assets in Section 3.3, and attribute classification accuracy in Section 3.4.

Category	Details
Model architecture	CLIP (ViT-B/32)
Interface	Gradio (prototype)
Hardware environment	NVIDIA RTX 3090 GPU
Input method	Single image
Average inference time	Approximately 45 seconds

Table 1. System Configuration

Valuation	Result
Semantic search accuracy (mAP)	62.57%
Cultural heritage material Accuracy	92.43%
Number of generated digital heritage items	12,131 items

Table 2. Evaluation Results of Semantic Analysis and Metadata Processing

4. Application Research Using the Platform

This section explores the application research conducted using the integrated cultural heritage platform. The developed system facilitates various innovative applications across multiple domains, demonstrating the practical utility and versatility of the standardized digital heritage management established in our platform. In museums the platform facilitates the identification of interrelationships among cultural heritage data through semantic graph analysis and supports thematic exhibition planning and the generation of AI-assisted digital restoration content as well as immersive visual content. In research it enables efficient comparative analysis based on typology material composition chronology and provenance while significantly reducing the time and cost associated with manual investigation. In addition, the integration of image-based recommendation systems and style transfer interfaces fosters interactive and participatory user engagement. These functionalities enhance the visitor experience and serve pedagogical purposes by enabling simulated restoration practices and promoting a deeper understanding of cultural heritage through experiential learning.

4.1 AI-Based Image Processing

4.1.1 Extension of Technologies for Cultural Heritage Analysis Using Style Transfer: Style transfer algorithm enables the visual reproduction of the aesthetic and atmosphere of a specific historical period by applying the sculptural or painterly style of that era to cultural heritage images. Furthermore, it can be used to create new artistic works inspired by traditional cultural heritage styles and has potential applications in the preservation and restoration of cultural heritage (Baek et al., 2024). In this research, we developed a style transfer algorithm capable of modifying and generating cultural heritage images according to specific objectives, thereby enabling the purposeful creation and utilization of data across various domains. By leveraging cultural heritage images as training data, the model effectively learned morphological features and visual patterns, and its generalization ability was enhanced to accommodate diverse application scenarios. Specifically, we optimized representation learning through knowledge distillation based on a pre-trained VGG19 network and the use of triplet loss. As a result in Figure 8, the proposed approach achieved more natural style transfers and demonstrated significant technical contributions in enabling seamless transitions of color and texture between cultural heritage images.

Figure 8. Application of the AI-based method within the cultural heritage detail page of the platform.

Original image Restored image

Figure 9. Application of the AI-based method within the cultural heritage detail page of the platform. (top) Quality restoration; (bottom) Stain removal.

4.1.2 Digital Restoration: This section proposes two core AI-based models aimed at the digital restoration of cultural heritage images, along with an intuitive user interface designed for practical application. The first model targets severely degraded images through a HAT-based Super Resolution approach. Based on an analysis of various degradation types, an Implicit Control mechanism was implemented to automatically adjust the restoration scale according to the characteristics of the input image, eliminating the need for manual resolution specification. As illustrated in Figure 9(top), the restored results demonstrate a clear improvement in image quality. The second model introduces a cultural heritage-specific Shadow Inpainting algorithm that addresses localized damage such as shadows, stains, and other contaminants commonly found in heritage imagery. In contrast to conventional inpainting techniques, which often fail to preserve structural details and may distort intricate textures, the proposed method effectively restores damaged regions by incorporating both structural features and visual coherence. The results in Figure 9(bottom) confirm the model’s ability to achieve high-quality visual restoration even in heavily contaminated areas. Both algorithms were integrated into a user-friendly Gradio-based graphical user interface (GUI) to facilitate easy use by non-experts. Users can simply upload images and execute restoration tasks through minimal interaction, with real-time feedback and no need for complex parameter tuning. This implementation underscores the practical value of the proposed techniques in cultural heritage preservation and research contexts.

4.2 Web-Based Management and Viewer

4.2.1 Reflectance Transformation Imaging: The web viewer supports interactive visualization of Reflectance Transformation Imaging (RTI), allowing users to examine surface details by adjusting the lighting angle. This enables precise analysis of fine textures on cultural heritage (Figure 10).

4.2.2 Giga Pixel: The Giga Pixel viewer provides access to ultra-high-resolution images (Figure 11), allowing users to view entire cultural heritage at a glance and zoom in to inspect fine patterns or areas of damage in detail.

Figure 10. Example of RTI viewer for web-based interactive exploration of surface details.

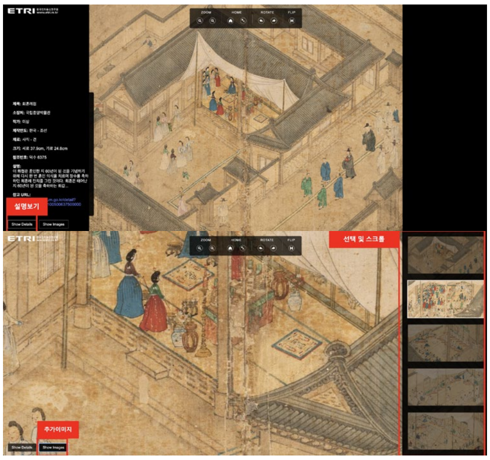

Figure 11. Giga-Pixel viewer interface supporting ultra-high-resolution zoom and detail inspection of cultural heritage.

Figure 12. GLB-based 3D viewer for real-time rendering and manipulation of cultural heritage models.

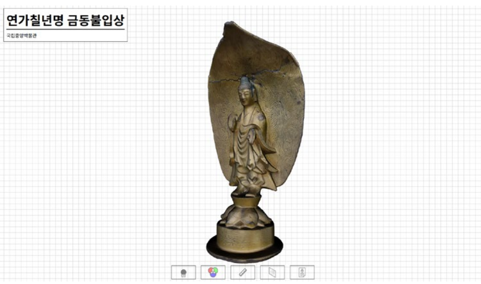

Figure 13. NXG viewer showcasing metadata-linked visualization and dynamic content integration.

4.2.3 GLB: 3D models in GLB format can be rotated, zoomed, and panned directly within the web environment, effectively visualizing the three-dimensional shape and structure of heritage objects (Figure 12).

4.2.4 NXG: The NXG-based viewer offers integrated viewing and comparison of multi-layered data, supporting comprehensive analysis and management of various types of cultural heritage data (Figure 13).

4.2.5 Quantitative Evaluation

Valuation	Result
Image quality and diversity (IS)	2.98
Image quality evaluation (FID)	26.91
Similarity to original objects (MS-SSIM)	82.62%

Table 3. Evaluation Results of AI-Based Image Processing

The table 3 presents the performance evaluation results from the official certification test for the core functions of the intelligent heritage platform. For each function—such as image quality and diversity, and similarity to the original—repeated tests were conducted, and average values were calculated. All items exceeded the required performance thresholds. Detailed descriptions of each evaluation metric are provided in Sections 4.1.1 and 4.1.2, and the corresponding quantitative results are illustrated in Figures 8 and 9.

5. Discussion

5.1 Strengths of the Proposed Platform

Figure 14(left) shows the main interface of Korea's national cultural heritage portal, "e-Museum," where users can search for artifacts using filters such as museum type, region, period, and excavation site. Both keyword and image-based search are supported, allowing exploration through themed image groups. However, the platform follows a directory-based structure, making it difficult to understand contextual or relational information between heritage items. Figure 14(right) shows the main interface of the integrated cultural heritage platform developed in this study. Leveraging AI, the platform offers various exploration methods including keyword search, similar item recommendations, and virtual restoration. Heritage information is visualized as attribute-based "assets," and a knowledge graph at the bottom enables intuitive navigation of semantic relationships. With additional content such as exhibition and project information, the platform provides an immersive and enriched exploration experience beyond simple information delivery.

Comparatively, while e-Museum adheres to a conventional information retrieval model based on predefined knowledge or keyword inputs, the proposed platform provides AI-powered visual information that supports heritage discovery through automated recommendations and relational analysis.

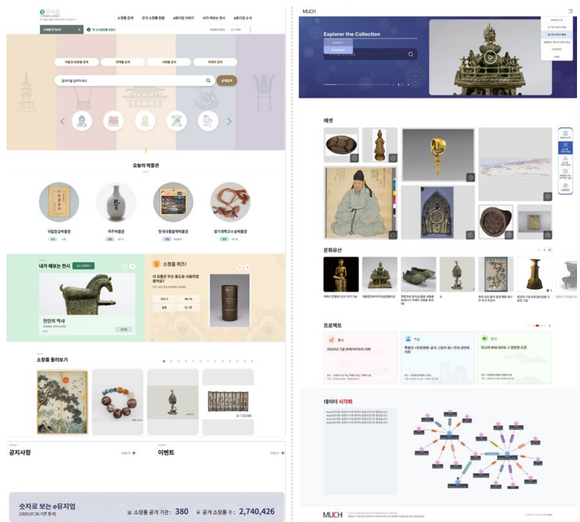

Figure 14. Comparison between the Korean e-Museum website (National Museum of Korea, n.d.) (left) and the proposed AI-based cultural heritage platform (right), highlighting differences in search functionality and visualization structure.

5.2 Limitations and Scalability

A major limitation in applying AI to cultural heritage is the lack of sufficient and balanced training data. Existing datasets are often fragmented or biased toward specific regions and periods which restricts the development of generalizable models. This limitation can lead to misclassification and limited recognition of underrepresented cultural assets, particularly in tasks requiring contextual or symbolic understanding. While the current AI models have been primarily trained on domestic datasets and may require retraining or domain adaptation for application to collections from other institutions or countries, the platform itself is designed with a modular and flexible metadata architecture. Therefore it is not bound to any specific national or institutional context and can be readily adapted for use across diverse cultural heritage environments provided that relevant data is available.

6. Conclusion

Our platform proposed and implemented an integrated digital cultural heritage platform that enables the structuring, standardization, visualization, and AI-based utilization of cultural heritage data in a unified framework. Traditionally, cultural heritage data had been generated and managed in a fragmented manner according to specific purposes such as exhibition, preservation, and education. To address this limitation, the proposed platform integrates such data within a single system, establishing a layered data structure (Work–Project–Instance–Item) that supports sustainable management and scalable operations.

The platform ensures interoperability and international compatibility by aligning with both domestic and international metadata standards, including EDM, Dublin Core, and Schema.org. It also features semantic graph-based visualization, allowing users to intuitively understand the relationships between cultural heritage objects, their associated metadata, and linked digital assets. Furthermore, the integration of a Gradio-based image recommendation system, style transfer algorithm, and AI-powered digital restoration technologies enables intelligent automation and user-centered accessibility across the entire lifecycle of data generation, exploration, and reuse.

Acknowledgements

This research is supported by Ministry of Culture, Sports and Tourism and Korea Creative Content Agency (Project Number: RS-2023-00219579).

References

Abid, A., Abdalla, A., Abid, A., Khan, D., Alfozan, A., Zou, J., 2019. Gradio: Hassle-free sharing and testing of ml models in the wild. In: *Proceedings of 2019 ICML Workshop on Human in the Loop Learning (HILL 2019)*, Long Beach, CA, USA. doi.org/10.48550/arXiv.1906.02569.

Baek, S., Cho, Y., Ahn, S, Choi, J., 2024. Algorithm development for texture and color style transfer of cultural heritage images. *Conservation Science in Museum*, 31(4), 55-70. doi.org/10.22790/conservation.2024.31.0055.

Dai, T., Cai, J., Zhang, Y., Xia, S. T., Zhang, L., 2019. Second-order attention network for single image super-resolution. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, Long Beach, CA, USA. doi.org/10.1109/CVPR.2019.01132.

Dong, C., Loy, C. C., He, K., Tang, X., 2014. Learning a deep convolutional network for image super-resolution. In: *Proceedings of Computer Vision–ECCV 2014: 13th European Conference*, Zurich, Switzerland. doi.org/10.1007/978-3-319-10593-2_13.

Hwang, H., Park, C. W., Kim, H. K., Lee, J. H., 2025. CATS: cultural-heritage classification using LLMs and distribute model. *npj Heritage Science*, 13(76), 1-13. doi.org/10.1038/s40494-025-01621-1.

Kim, H. K., Hwang, H., Choi, J., Park, C. W., Lee, J. H., 2024. Ontology-based Data Structure and Management System for Digital Heritage Management. In: *Proceedings of the Summer Annual Conference of IEIE*, Jeju, Korea.

Li, X., Guo, Q., Abdelfattah, R., Lin, D., Feng, W., Tsang, I., Wang, S., 2023. Leveraging inpainting for single-image shadow removal. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*, Paris, France. doi.org/10.48550/arXiv.2302.05361.

Lim, B., Son, S., Kim, H., Nah, S., Mu Lee, K., 2017. Enhanced deep residual networks for single image super-resolution. In: *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, Honolulu, HI, USA. doi.org/10.48550/arXiv.1707.02921.

Lee, J. H., Park, C. W., Kim, H. K., 2024a. Digital Transformation of Cultural Heritage for Various Museum Applications. In: *2024 International Conference on Electronics, Information, and Communication (ICEIC)*, Taipei, Taiwan. doi.org/10.1109/ICEIC61013.2024.10457249.

Lee, J. H., Park, C. W., Kim, H. K., 2024b. Huge Content Data Management for Numerous Applications in the Museum. In: *2024 Fifteenth International Conference on Ubiquitous and Future Networks (ICUFN)*, Budapest, Hungary. doi.org/10.1109/ICUFN61752.2024.10625592.

National Museum of Korea, n.d.: National Museum of Korea e-Museum. https://www.emuseum.go.kr/main

Neo4j, n.d.: Neo4j Official Website. https://neo4j.com

Park, C. W., Kim, H. K., Lee, J. H., 2024. Research on Digital Cultural Heritage Expansion Using AI Technology. In: *2024 Fifteenth International Conference on Ubiquitous and Future Networks (ICUFN)*, Budapest, Hungary. doi.org/10.1109/ICUFN61752.2024.10624889.

Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., ... Sutskever, I., 2021. Learning transferable visual models from natural language supervision. In: *International conference on machine learning. PmLR*. doi.org/10.48550/arXiv.2103.00020.

Teichmann, M., Araujo, A., Zhu, M., Sim, J., 2019. Detect-to-retrieve: Efficient regional aggregation for image search. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, Long Beach, CA, USA. doi.org/10.17863/CAM.42014.

Vo, N., Jiang, L., Sun, C., Murphy, K., Li, L. J., Fei-Fei, L., Hays, J., 2019. Composing text and image for image retrieval-an empirical odyssey. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, Long Beach, CA, USA. doi.org/10.1109/CVPR.2019.00660.

Yu, J., Lin, Z., Yang, J., Shen, X., Lu, X., Huang, T. S., 2019. Free-form image inpainting with gated convolution. In: *Proceedings of the IEEE/CVF international conference on computer vision*, Seoul, Korea. doi.org/10.48550/arXiv.1806.03589.