


# Model-Driven Integration of Deep Learning for Artifact Classification in Museum Information Systems

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## ABSTRACT

Museum Information Systems (MIS) often rely on manual classification and keyword search, limiting accuracy and scalability. Deep learning offers a solution, but effective integration requires alignment with curatorial workflows. This study proposes a model-driven framework for integrating Convolutional Neural Networks (CNNs) into MIS to enhance artifact classification and retrieval. A prototype was built using ReactJS, Django, and TensorFlow, and it was trained on a curated subset of The Met's Open Access Images. The system employs a Hybrid-E Loss for improved classification accuracy. The model achieved 94.3% classification accuracy and real-time retrieval latency below 100 ms, with throughput exceeding 14 queries per second. The framework successfully bridges AI performance with curatorial logic, demonstrating a scalable and interpretable solution for digital heritage systems.

## KEYWORDS

Museum Information Systems, Deep Learning, Convolutional Neural Networks, Model-Driven Architecture, Artifact Classification, Cultural Heritage, Image Retrieval, Semantic

## MODEL-DRIVEN INTEGRATION OF DEEP LEARNING FOR ARTIFACT CLASSIFICATION IN MUSEUM INFORMATION SYSTEMS

Metadata standards are central to museum information systems (MIS), yet manual cataloging is still the dominant practice—a process that is slow and error-prone (Dörr, 2002). Extensive digital collections magnify these issues. Inconsistent or incomplete tags impede the discovery of artifacts, and most keyword searches often miss essential items. Convolutional neural networks (CNNs), powered by deep learning, have revolutionized image classification, driving error rates way down across many vision tasks, especially models trained on large datasets like ImageNet (Russakovsky et al., 2015). In the cultural heritage domain, early work shows that CNNs can identify artifacts with over 70% accuracy large and diverse datasets (Winterbottom et al., 2022). Such results imply an obvious opportunity: machine-assisted, image-based tagging can accelerate and enhance the quality of museum cataloging.

DOI: 10.4018/IJITWE.387650

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The integration of deep learning into operational MIS is often ad hoc. At times, custom scripts bypass existing semantic models and curation workflows, leading to increased management overhead and risks of semantic drift. To address this, the authors propose a model-driven bridge that formally embeds deep learning modules into MIS. By defining metamodels that capture curation semantics and mapping them to CNN-based components, the authors aim to improve classification accuracy, enhance system robustness, and achieve faster retrieval.

As collections grow, the scalability problems associated with traditional MIS, which are based on human input, make them unworkable (Arnold & Geser, 2008). The task of cataloging artifacts is very time-consuming and susceptible to inconsistency or subject bias (Bachi et al., 2022). The lack of interoperability results from fragmented metadata standards, often stemming from different curatorial practices in other institutions. Additionally, most retrieval systems in many MIS platforms depend on keyword matching and do not have semantic understanding. Thus, it is difficult for users to find relevant artifacts, especially when metadata is sparse or erroneous (Doerr, 2001). A related problem is that the static nature of traditional MIS reduces its adaptability, particularly content-based search capabilities, which are becoming popular requirements for modern users. Moreover, it takes expertise, time, and money to maintain and upgrade these systems, posing another barrier to small or budget-constrained museums (Marty, 2007). The inherent challenges make it clear that these efforts could greatly benefit from automated, intelligent solutions that remain directed toward the practice of museums, providing workflows that improve efficiency and access.

Deep learning, especially CNNs, showed powerful performance in the domain of image recognition tasks, exceeding traditional feature-engineered methods (Krizhevsky et al., 2017). In the context of the museum domain, artifacts tend to be characterized by complex and delicate patterns, textures, and styles that are difficult to capture through conventional metadata-based systems. Instead, artifact images can be directly used to learn hierarchical visual features through CNNs, enabling accurate classification across diverse categories and historical periods (Gîrbacia, 2024).

Additionally, deep learning models can be fine-tuned with a small museum-specific dataset, making them transferable to different institutional needs or constraints. Nevertheless, such models need to be integrated into existing MIS. Without structured guidance, deep learning modules can become isolated from museum workflows and curatorial logic.

This problem is addressed by a model-driven approach. This approach defines high-level metamodels that formalize both system requirements and data semantics (Kleppe et al., 2003). Model-driven engineering (MDE) reduces the gap between technical implementation and domain-specific expectations of existing business processes by systematically mapping deep learning integration to them. This approach not only enhances system maintainability but also encourages connectivity among different museum systems, which is key for preserving cultural heritage and sharing knowledge (Kleppe et al., 2003).

This study is driven by three central research questions:

1. How can a model-driven framework effectively integrate deep learning techniques into MIS without disrupting traditional curatorial workflows?
2. To what extent does deep learning-based artifact classification outperform traditional manual or keyword-based classification methods regarding accuracy and retrieval speed?
3. How does a model-driven, deep learning-enhanced system impact user satisfaction for museum professionals and visitors?

The primary objective of this study is to develop and evaluate a model-driven framework that integrates deep learning techniques, specifically CNNs, into MIS to enhance artifact classification and content-based image retrieval. The framework aims to align artificial intelligence components with existing curatorial workflows and semantic metadata standards, ensuring technical performance and interpretability. By embedding CNN-based models within a modular, service-oriented architecture, the

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