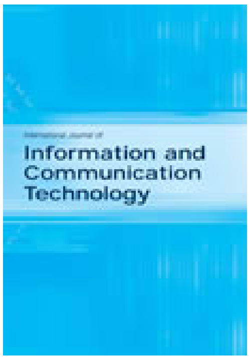

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Artificial intelligence for cultural heritage: digital image processing-based techniques and research challenges

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Abstract: Digital image processing and analysis play a crucial role in processing and interpreting visual data, enabling significant advancements in computer vision, pattern recognition, and various technological applications. Image processing has also helped the area of cultural heritage as it has emerged as a transformative tool, offering innovative solutions for preserving, documenting, and promoting cultural heritage. Cultural heritage encompasses the tangible and intangible expressions of a society's history, and values for maintaining identity, and inspiring future generations. In the research domain of cultural heritage, this systematic literature review explores the digital image processing and analysis techniques for cultural heritage, focusing on their applications in image segmentation, object detection, digitisation, restoration, and enhancing image qualities of various cultural artefacts. The review examines the datasets commonly used in these fields. We have discussed the various applications of AI along with open research challenges which may serve as future research directions. By exploring these trends, the study provides insights into how AI technologies can contribute to the sustainable and responsible preservation of cultural heritage for future generations.

Keywords: digital image processing; cultural heritage; artificial intelligence; computer vision; research challenges; heritage applications.

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1 Introduction

Artificial intelligence (AI) has revolutionised the world by automating complex tasks, enabling data-driven decision-making, and transforming industries across healthcare, finance, and transportation. In computer vision, AI has dramatically improved image and video analysis, enabling technologies like facial recognition, autonomous vehicles, and medical imaging. These advancements have not only enhanced efficiency and accuracy but also opened new possibilities for innovation and problem-solving in various fields. Focusing on cultural heritage, it serves as a bridge between the past, present, and future, providing a collective identity to societies while shaping the character of generations to come. It encompasses tangible elements like monuments, artefacts, and manuscripts, as well as intangible factors including languages, traditions, and rituals. Preserving this heritage is vital for maintaining a sense of continuity and fostering cross-cultural understanding. However, traditional methods of conservation and dissemination face challenges, such as resource constraints, physical degradation, and limited accessibility. In recent years, AI has affected evolutionary changes in various fields and areas of interest including cultural heritage. AI's potential lies not only in preserving the past but also in innovatively re-imagining its accessibility and relevance in the modern digital era. Advanced technologies enable innovative solutions for addressing long afflicted issues in the field, providing advanced capabilities for conservation, analysis, and engagement. AI technologies have increasingly found applications in the cultural heritage sector, addressing challenges related to documentation, restoration, analysis, and dissemination. Machine learning (ML) models and deep learning (DL) architectures have revolutionised the way heritage sites are analysed and restored, offering precision in damage detection and predictive maintenance. Additionally, natural language processing (NLP) techniques are being employed to decode ancient texts, translate historical manuscripts, and preserve endangered languages. AI-driven image recognition has made it possible to digitise and catalogue vast archives, ensuring that valuable cultural artefacts are not lost to time.

Recent years have witnessed a surge in research interest and funding aimed at leveraging AI for cultural heritage. From supported agencies initiatives to private sector collaborations, a growing number of projects are exploring innovative AI-driven solutions. This momentum has also spurred academic research to analyse emerging trends, evaluate the impact of AI applications, and propose methodologies for integrating AI with traditional conservation techniques. The current age of cultural heritage, including AI, ML, and DL has made spectacular progress in the 21st century. These technologies offer strong arrangements for automatic action and enhanced results, it can facilitate processing, analysis, and simulate experiences. For the existing AI technologies, it can be stated that nowadays their application in the field of cultural heritage is not an experiment, but a need (Janković Babić, 2024). Currently, governments, NGOs, and global research institutions use AI to digitise and preserve heritage structures and relics. Cultural heritage refers to the tangible, intangible and natural cultural heritage it is important to identity, passed down through generations, human diversity and support economic development. Various elements of cultural heritage include social relationship, material culture, spiritual culture and traditional language (Monna et al., 2021).

1.1 Background

Cultural asset is an essential component that protects people's experience as well as the ideas of future generations of people. New technologies of AI are emerging as the breakthrough ways of enhancing preservation analysis and restoration of cultural heritage (Sousa et al., 2024). Culture remains an important factor in helping society define its uniqueness while creating awareness about other societies. Nevertheless, there are problems in the conservation and analysis of cultural objects that include natural aging, hostilities, and financial constraints. Recent development of AI, such as ML and DL has created the possibilities of the computerisation of preservation work and analysis using digital historical data (Zhang et al., 2022a). Cultural heritage preservation and study from early started from the correlations of archaeology, Anthropology, and history and earlier traditional methods for documenting, analysing and restoring cultural property and sites remained a challenging task. Over the years, the field started moving towards methods that include the application of sciences especially with the introduction of technology (Abgaz et al., 2021). Such change has notably resulted from AI which create new opportunities to save, comprehend, and advocate cultural heritage (Pisoni et al., 2021). Example of some cultural heritage image show in Figure 1.

Figure 1 Examples of some cultural heritage image (see online version for colours)

Source: pixels.com

However, the integration of AI into the domain of cultural heritage remains as a new area of study with a lot of potential for further exploration of both opportunities and limitations. This paper aims to provide a detailed analysis on development, issues and future trends in this field. The findings underscore the transformative potential of AI while advocating for responsible, inclusive, and sustainable approaches to its adoption in cultural heritage initiatives. In this research study, our objectives are as follows: To synthesise a more comprehensive understanding of research trends based on datasets, methodologies, and applications, with the aim of introducing technology to cultural studies and encourage academic collaboration for the conservation of cultural heritage around the global.

1.2 Significance and motivation

The increasing focus on the application of AI in cultural heritage results from the objective possibility of solving some of the most significant problems in this area. The field workers especially in cultural heritages and archaeologies, propagate with colossal responsibilities of overwhelming quantities of records, relics and sites. Traditional approaches may be efficient, but they are normally slow, costly and labour-intensive, and not easily replicable. AI offers client solutions to automate and enhance these processes leading to better and efficient way to preserve the processes. This topic is important since it facilitates collaboration between technological and humane subjects. AI not only helps in the preservation of physical and digital collections but also assists in the dissemination across audiences, for scholars, educators, and general population. For example, such technologies allow tourists to explore historical places online, accurately translate the contents of books and documents, and make reliable forecasts about the material's deterioration, so that museums and libraries can preserve the books for generations to come. The reason why furthering one's knowledge of this subject is rather stimulating is the practical applicability of the issues investigated. AI technology is continuing to become trendier by the day and now cultural heritage institutions are embracing it as the future. In addition, the stakes of paradigm shift to incorporation of AI into this realm like cultural relevance and safeguards against the biases of AI algorithms form major and attractive topics of discussion and research. There is a need for a systematic literature review into the use of AI in CH since such a review will act as a knowledge database as well as present future directions for research in this active and relevant subfield of CS.

1.3 Contributions

Our main contributions are as follows:

- *Integration of diverse fields:* Hence, this review work fits into the niche of both AI and cultural heritage, thus presenting information on the synergy between the two.
- *Temporal scope of studies:* It also systematically examines papers published between 2020 and 2024, covering last-mile delivery innovations in ML and DL technologies.
- *Exploration of datasets:* The review focuses on different datasets that are applied in cultural heritage applications, their properties, problems, and potential improvements.
- *Application insights:* It covers many AI topics pertinent to CH such as data preservation, restoration, visualisation, education or communication to the public.

- *Research challenges and future directions:* Remaining gaps of the research include the scarcity of data and the assigning of ethical and technological concerns, along with further recommendations.

1.4 Paper organisation

This paper is structured as: Section 2 presents the knowledge of existing literature based on ML and DL approaches from 2020 to 2024. Section 3 provides the details of available datasets. Section 4 shares the applicability scope of AI and CH in domain. Section 5 gives the open research challenges pointed towards future directions. Lastly, section 6 provides the conclusion of this study.

2 Review of existing studies

In this section, analysis of existing studies is presented to define and explain the technique, dataset and model have done in this field. A significant body of research has explored the application of ML and DL in the domain of cultural heritage, underscoring their transformative potential in solving complex challenges. ML techniques have been widely used for tasks such as artefact classification, historical document analysis, and predictive modelling for conservation strategies. Meanwhile, DL models have demonstrated unparalleled accuracy in processing unstructured data. Their ability to learn hierarchical representations has proven invaluable in applications such as high-resolution image restoration, ancient text translation, and automated damage detection in artefacts and monuments. Collectively, these studies highlight the growing role of ML and DL in reshaping the landscape of cultural heritage preservation and research.

2.1 Approaches of computational models

Concepts of computational models include a comprehensive spectrum of strategies selected to address a range of issues with the help of computers. These are rule based systems where the logic for decision making is created in advance, statistical models where records and ways of working record patterns that are common Statistic approaches, ML approaches which include supervised learning (SL), unsupervised learning (UL) and reinforcement learning, DL models which incorporate neural networks for complex and high dimension. New areas also study neuro-symbolic systems with reasoning from logic and learning from data and evolutionary algorithms drawn from the concept of natural selection for problems of optimisation.

2.2 Supervised learning

SL aims to learn a mapping function f: $Y \rightarrow Z$ from an input space Y to output space vector Z, with a sequence of labelled input and output pairing $\mathcal{L} = \{(y_i, z_i) | i = 1, 2, 3, \ldots, N\}$, utilised for training data, drawn independently from a joint probability solution $p(y, z)$. The function f is learned by minimising a loss function $\ell : Z * Z \rightarrow \mathbb{R}$, which measures the penalty for wrong predictions. SL is broadly categorised into regression where $Z \subseteq \mathbb{R}$, and classification, where Z is a discrete set.

2.3 Unsupervised learning

UL, on the other hand, deals with learning patterns or structures from data $U = \{x_i|i = 1, 2, 3, \ldots, N\}$, where the output labels are unknown. The goal is to uncover a representation $g: X \rightarrow Z$ where Z represents a meaningful latent space. A common task based on UL is Clustering, where data points are grouped into clusters $\{C_k|k = 1, 2, 3, \ldots, N\}$ such that the intra-cluster similarity is maximised, and inter-cluster similarity is minimised. Clustering algorithms such as k-means and hierarchical clustering often depend on distance metrics $d(x, y): X * X \rightarrow \mathbb{R}^+$ to define similarity.

2.4 Semi supervised learning

SSL operates on dataset $D = \mathcal{L} \cup U$ where $\mathcal{L}$ is a small set of labelled data and U is a large set of unlabelled data. SSL algorithms aim to handle the structure of $p(x)$, the marginal distribution of input features, to improve the learning of $f: X \rightarrow Y$ using both $\mathcal{L}$ and U. Methods such as self-training, graph-based approaches, and consistency regularisation are commonly used in SSL.

2.5 Existing studies with ML

The typical process of a ML model involves several key stages, as shown in Figure 2. Data preparation is the first stage of the ML process, where data is obtained to describe the necessary features, so the model considers the nature of the problem domain. The data then gets pre-processed, which means that there is removal of missing values and encoding of nominal features as well as scaling of the numeric features and removing of inconsistencies or noise (Alghamdi et al., 2024). After this, feature selection is then employed to filter out the most relevant features and exclude from the model all those that present low influencing power, this improves not just the model's speed but also its effectiveness (Towarek et al., 2024). The pre-processed data is then split into the train and test data during data splitting where the model identifies patterns of data in train set can predict the outcome on the test set. The middle part of the process is called model training, during which the chosen ML algorithms are trained on the training data: main parameters are tuned, and error is minimised to obtain a prediction model. Finally, the model is evaluated using performance measures with the accuracy, precision, recall the F1-score and the mean square error to validate the consistency of the trained model for practical applications (Janković, 2020). The use of ML algorithms held in various tasks and research challenges in cultural heritage. Table 1 shows the analysis of existing work in this domain.

Diverse classification algorithms under analysis were used to compare results of CH image classification; artificial neural network based multiple layer perception algorithm used in this paper analysed yielded the highest CH images classification accuracy of 94%, while other algorithms yielded an accuracy of 82% (Abgaz et al., 2021). ML methods have been applied to Asian regions such as North-East, Penang Island, Malaysia (Mohamad et al., 2024). Five supervised algorithms which are: artificial neural network, random forest, support vector machines, k-nearest neighbours (kNN), and logistic regression (LR) have been applied and achieved 85% accuracy. Selected ML-based algorithm have been applied to conduct archaeological predictive modelling for the

Canton of Zurich, Switzerland (ResearchGate, 2024a). RF, an example of techniques from ensemble learning family, is used with the dataset of the Roman Age archaeological sites. The goal of the study is to examine the spatial likelihood of the existence of Roman settlement in the region and develop a probability map of the site and achieve 72% AUC. Employed ensemble model random forest to classify (ResearchGate, 2024b) the semantics of point clouds produced by UAV photogrammetry and GNSS surveys, for 3D reconstruction of the Temple of Hera, Italy following the use of eight GCPs. ML models have been applied for recognising handwriting script of Bima using LBP feature extraction and kNN classification-method with a maximum accuracy of 86.056% achieved by nine radius value LBP (Fidatama et al., 2023). Among cultural heritage artefacts, hand-woven and machine-woven carpets, have also been identified using ML (Isik et al., 2024). Three senior carpet researchers obtained 48 morphology characteristics from 359 carpets and used the ML method to categorise them. ANN/MLP and SVM had the best classification results with an accuracy of 96.66%. The two levels yielded and accuracy of 98.61% for 48 features and 97.77% for 28 features showcasing that AI techniques are applicable to carpet classification. ML for cultural heritage including classification of artefacts, analysis of historical documents, conservation decision making using predictive modelling have employed SVM and RF to classify artefacts based on the cracked material properties and geometry and to yield improved results as opposed to the conventional techniques in museums (Mallik and Kumar, 2024). As for the image distances, multi-dimensional scaling algorithm is employed to map them into space of Gram matrices in which the coordinates of the images are calculated used for the reconstruction of 3D models of cultural heritage landmarks clustering techniques allow the discovery of new connections between artefacts and historical sites (Zheng et al., 2021). This analysis shows that ML can be effectively used to solve a wide range of problems in cultural heritage, and the importance of its approaches to finding practical and scalable solutions.

Figure 2 A framework showing typical approach of application of ML algorithm (see online version for colours)

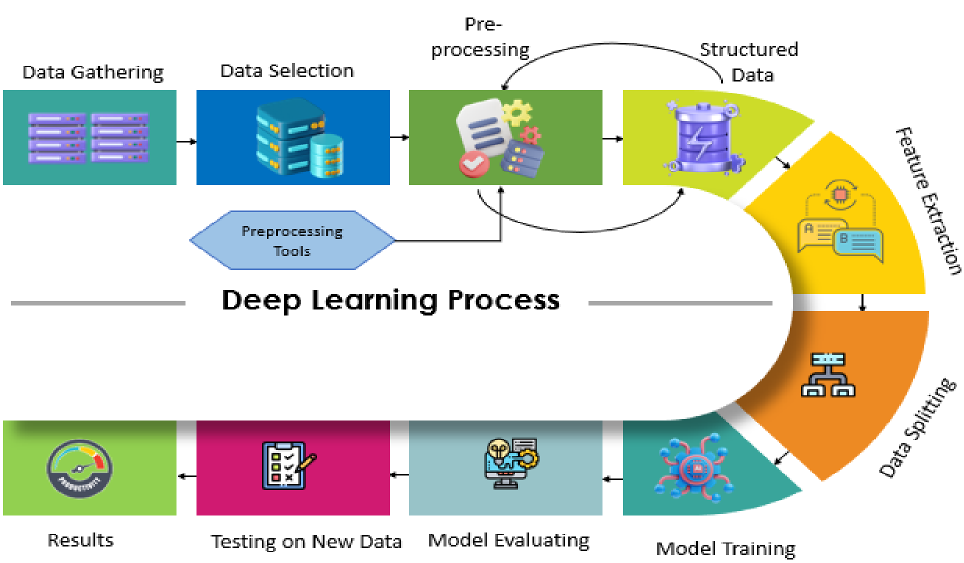


Table 1 Existing studies with ML models

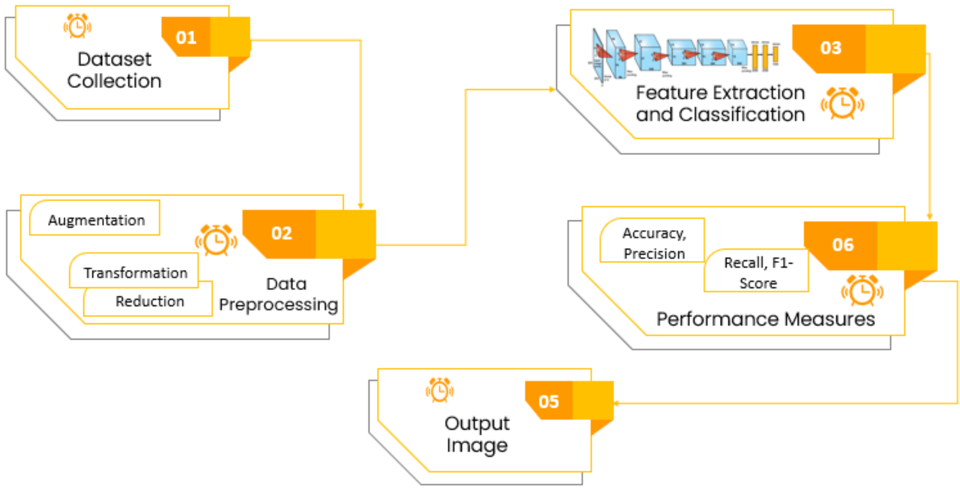
Ref.	*Year*	*Models*	*Dataset*	*Research area*	*Results (acc %)*
Janković (2020)	2020	MLP	Image dataset	Image classification	94
Mohamad et al. (2024)	2020	SVM	Prewar shop house heritage property	Historical pattern	85
ResearchGate (2024a)	2021	RF	Archaeological sites dating back	Image classification	72
ResearchGate (2024b)	2022	Random sample consensus	UAV: DJI Mavic 2 PR	3D reconstruction	80
Fidatama et al. (2023)	2024	KNN	Image handwritten Bima script	Recognising handwriting script	86
Isik et al. (2024)	2024	ANN	Hand-woven and machine-woven carpets	Carpet classification	98

2.6 Existing studies with DL

DL, a subset of ML, uses artificial neural networks with many layers to analyse and learn from large amounts of data. It excels at tasks like image and speech recognition, NLP, and more. DL-based classification model commonly go through several stages as illustrated in Figure 3. First, the acquisition of dataset is made to obtain a very large set of input belonging to the classes. This is succeeded by data pre-processing whereby data is normalised, resized or augmented so that it performs well during model training. After pre-processing, data is divided into training, validation and testing to determine the model's ability to generalise from set data. Feature extraction is a crucial step where feature or pattern of the input data useful for classification is determined (Mallik and Kumar, 2024). While using DL architecture, an input is provided to the model. The data then moves through one or more of the convolution layers used to extract spatial features or edges, specific texture and the like. These are succeeded by pooling layers such as max pooling or average pooling to lower the spatial extent and retain the feature. It is likely that this process of convolution and pool layering can be repeated several times to capture hierarchy features. After that, in the flatten layer, the obtained data is made as a one-dimensional vector for further transferring to the output layer in which the model characterises class probabilities or labels (Monna et al., 2021). Lastly, the performance of this proposed model is reviewed and analysed using performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC for evaluating its capability of classification (Zheng et al., 2021).

Considering the DL models, CNN is widely used for image processing and computer vision. In addition, several pre-trained models are also preferred to be used in cultural heritage research based on transfer learning. Table 2 shows the analysis of existing work in this domain. The CNN model has been trained and tested with accuracy on two set of data with better performance on smaller set and also demonstrated success in imbalanced set of cultural heritage images with an assumption that increasing the class imbalance will have the same impact on the accuracy of the model and achieved 90% accuracy (ResearchGate, 2024c).

Figure 3 A framework showing typical approach of application of DL (see online version for colours)



In the study (ResearchGate, 2024d), images of architectural heritage are classified using convolutional neural networks which enhances management of datasets and searching for an item. Several image pre-trained networks: pre-trained networks GoogLeNet, Resnet50 and Resnet18 are applied to the public dataset of Cultural Heritage images, achieving promising results with accuracy levels of 87.91%, 95.47%, and 95.57% respectively. Recognition of cultural heritage building is an important research challenge. A new hierarchy net and BCNN end-to-end network for the main and subcategories of buildings in the urban environment using the style of facade images (ResearchGate, 2024e). It employs a pyramid structure of course and fine and a new multiplicative layer which allows for enhanced fine prediction. The model performs better than baseline CNN for urban building classification and other multi-level classification tasks and achieved 93. One of the mostly widely used DL algorithms of CNNs is proposed to directly learn and abstract discriminative features from the augmented cultural heritage images (Rehman et al., 2023) adopts the. Two methods of image variability are rotation and scaling, as well as flipping where an image is flipped horizontally. The CNN-based model even reaches a top level of classification accuracy and distinguishes cultural artefacts, artworks and historical scenes precisely. The purposed model achieved 93% accuracy. In the applied part of the study (ResearchGate, 2024f) DL architectures are applied in the identification of features from profiles of Iberian wheel made pottery vessels in archaeological site. Overall, the established model attains a mean accuracy of 0.96, larger than other ML techniques. This paradigm shift brings new techniques to automatic feature representation and classification within the Archaeology subfield. A new framework proposed (ResearchGate, 2024g) the SOM of an ANN for the classification of Javanese batik motifs, using statistically significant accuracy improvement when using a number of different feature-extraction techniques and achieved 80%.

Egyptian culture is one of the most famous cultures in the world due to its rich culture and pyramids. This study (ResearchGate, 2024h) is a research on CNN for segmenting and categorising images of ancient Egyptian hieroglyphs. Three types of CNN architectures are discussed and a dedicated CNN, named Glyphnet, was developed. The researchers concluded that the Glyphnet had better performance, better training, and lower computation than comparable methods. Mask-RCNN was also employed by the study for segmentation of ancient hieroglyphs and achieved best accuracy. This study creates (ResearchGate, 2024i) a Cantonese opera audio database and presents a classification method utilising the CoGCNet model based on genre classification networks. In this model, mel-frequency cepstrum input has been employed, and a cascade fusion CNN has been used to enhance the accuracy for classification. Experimental result reveals high accuracy with 95.69% of precision, 95.58% of recall and 95.60 % of F1-value more than the benchmark neural network models.

Table 2 Existing studies with DL models

Ref.	*Year*	*Models*	*Datasets*	*Research area*	*Result (acc %)*
ResearchGate (2024c)	2020	CNN	Architectural-heritage-elements	Image classification	90
ResearchGate (2024d)	2020	CNN	GoogLeNet, ResNet18, and ResNet50	Image classification	95
ResearchGate (2024e)	2020	BCNN, hierarchy net	MexCulture142	Urban environment using the style of facade images	93
Rehman et al. (2023)	2021	CNN	Architectural heritage	Augmented cultural heritage images	93
ResearchGate (2024f)	2021	ResNet	Binary image database	Archaeology subfield	96
ResearchGate (2024g)	2022	ANN	Custom dataset	Javanese batik motifs classification	80
ResearchGate (2024i)	2022	LSTM	Cantonese opera datasets	Genre classification	95
ResearchGate (2024j)	2023	CNNAR	Paris500K and Corel5K	Architectural images of diaspora Chinese	98
ResearchGate (2024k)	2023	VGG	Wooden cultural heritage	Image classification	96
Subhash et al. (2024)	2024	Bi-LSTM	ILI Indo-Aryan dataset	Image classification	93

Chinese culture is rich tapestry of ancient traditions, art, philosophy, and innovations that have influenced the world. DL algorithms have been applied to identify the architecture of the Chinese overseas dimension in Jiangmen City and Guangdong Province China (ResearchGate, 2024j). The research obtained 5,073 architectural images of diaspora Chinese in 64 villages and 16 towns. In the implementation of the CNNAR Framework, the depth learning method was applied to develop the framework. These results indicate a classification accuracy of 98.3% in PCR for heritage image datasets comprising of JMI Chinese diaspora architectures; as well as a mean Average Precision of 76.6%. When tested on two public datasets Paris500K and Corel5K, the proposed scheme, namely

CNNAR retrieval framework, documents accuracy levels of 71.8% and 72.5% respectively. An optimisation framework (ResearchGate, 2024k) for detecting the surface damage of an article is developed using a classification algorithm based on a DL model for real-time surveillance of cultural heritage. With the help of 4,000 images from sites, between 94.00–96.50% was achieved when using the model only. The best performance was demonstrated when applying gradient-weighted class activation mapping. Indo-Aryan languages are identified in this study (Subhash et al., 2024) using data augmentation with a deep-learning ensemble model. Four models are chosen and out of them the Keras embedding performs well include Bi-LSTM, Bi-GRU GRU and CNN-Bi-LSTM. The best performance is obtained by the soft voting classifier, which resulted in a 93% F1-score. The results are evaluated against other baseline models through macro F1, recall, accuracy and precision.

3 Datasets for culture heritage analysis

The dataset and its preparation are very important for any AI-driven task. In the field of cultural heritage, diverse datasets have been created and are being used in this research domain. We present here a brief overview of each dataset and then share the comparative Table 3 highlighting the main features of the datasets which may serve as a ready reference for the researchers in selection of the desired dataset for their research studies in the domain of use of AI including ML and DL in the cultural heritage. Figure 4 shows the sample images collected from datasets.

3.1 OmniArt

Since 2014, the Rijksmuseum added more than ninety thousand photographic reproductions of artworks to its newly developed digital assets. The Metropolitan Museum of Art launched Open Access, which puts images of works in the public domain into the public domain. The Met also added tags to images for artist, title, period, medium, materials, and dimensions. Expanding the current set of tested collections, the meta-tagged dataset of 432,217 image reproductions was created from the Rijksmuseum Collection, Met, and the Web Gallery of Art (WGA). A better quality of annotations was attained and labels which created the confusion were excluded (ResearchGate, 2024l).

3.2 WikiArtPaintings

WikiArtPaintings, a dataset, represents a wide range of images, collected from Flickr for paintings analysis in art and photo-processing tasks. They have annotations for 80,000 Flickr photographs under 20 style classes and in addition to 85,000 paintings under 25 style or genre classes. This dataset is suitable for a broad range of studies, with a clear focus on style classification, genre identification or image search, thus being an indispensable tool at the cutting-edge synergy of art and AI. Several works relying on this dataset have expressed high classification accuracy that test the quality of the dataset as well as the labelling process. WikiArtPaintings is the most useful for the development of DL for tasks such as image recognition, style transfer, and cultural analysis, and benefits the field of art computational analysis (Karayev et al., 2014).

3.3 Behance Artistic Media

The Behance Artistic Media (BAM) dataset is a large and diverse collection facilitate to image understanding and artistic media. It consists of more than 2.5 million images downloaded from Behance with 1,112 descriptive tags for images' inherent features. These include 20 different metrics ranging from content, style, composition to provide richer image information. This inherent labelling can also be done manually but has been automated in this work to enable standardisation across perhaps a large dataset. Besides the inherent metrics, there are 393000 binary attribute labels collected by crowd to increase the original data quality. These labels are useful for such purposes as attribute classification, aesthetic prediction, and patterning of artistic media content for easier analysis. Additionally, of the 74k images in the dataset, 67k of them have associated short text descriptions and captions contributed by the crowd. This textual data serves as a great starting point for image captioning research, multimodal learning, and image-to-text task, and holds potential for developing more precise and contextually-wise AI models (Xie et al., 2017).

3.4 IconArt

IconArt is a specific dataset created for iconography and classification problem within the field of art analysis. It contains a total of 5,955 painting images, which is classified as 2,978 images of training set and 2,977 images of the testing set. For the usage of this dataset, the class identifiers, detailed annotations and even bounding box coordinates of the objects depicted in the paintings are perfect form under classification methods. Another interesting characteristic of IconArt is the iconographic classes as bounding box annotations are provided for 1,480 of the 2,977 testing image samples. These annotations accommodate seven iconographic classes, thereby allowing for analysis at increasingly detailed levels of artwork. Perhaps, in combination with facades, this can enable person-independent fine-grained evaluation since the detailed bounding box annotations are suitable for object detection tasks, semantic segmentation, and fine-grained visual recognition in the art domain. The IconArt collection is a valuable reference for enhancing scholarly inquiry into art history and iconometry, as well as for training AI-driven algorithms to analyse, categorise, and interpret artistic work that bears historical and cultural meaning (Gonthier et al., 2019).

3.5 PrintArt

Specifically, the PrintArt database, MONOART in short, is a set of artistic grey-scale images which are used for the works in the field of vision computer, such as detection, classification and pose recognition. It is a collection of 988 images, all of which include accompanying tags to enable multiple analysis procedures. This approach encompasses global semantic tags, which represent global theme or subject of the image, and local arrangement tags that present spatial relation and position of elements in the referred artwork. Another aspect of the PrintArt dataset is WIDD, which consists of 75 visual classes where 27 classes are related to thematic content of the image meaning component, including the genre of art. Furthermore, 48 visions classes are detected as part of bounding extents, which contain features that define certain objects or figures captured in art. Of these 48 classes, 37 classes are provided with additional pose labels showing the position of the human figures and three classes with the position of animal figures in the artwork. The dense annotations provided by PrintArt facilitates building models for intricately modelling visual data and for performing the elaborate computations that is required when it comes to tasks such as pose estimation, object detection and semantic segmentation in artistic contexts. This dataset is especially significant for the analysis of the interaction of artistic trends and the images of people and animals and contains the necessary data for further development of AI methods for art analysis and interpretation (Carneiro et al., 2012).

3.6 Rijksmuseum

The Rijksmuseum dataset is freely available in Linked Open Data format based on Europeana Data Model which constitutes one of the leading art museums globally The Rijksmuseum Amsterdam. This dataset contains paintings and photographs as well as ceramic, furniture, and other historical items. It provides an authoritative and structured digital narrative of the Museum's collection which can be interrogated and explored by scholars and developers alike. The source contains 3,593 objects and images with the possibility to add metadata about the objects and their characteristics including the kind of object, the artist, the period, material and other objects related to this object. Consequently, the Rijksmuseum dataset becomes an important source of corresponding fields of study concerning cultural heritage, art history, and digital humanities to understand the development of styles and historical objects. Combined with its availability of public domain, the Rijksmuseum dataset is also used in fields of ML for creating models applied to image categorisation, object recognition and visualisation in terms of study of paintings and history assets. It becomes an important tool in supporting the distribution and increase in visibility of cultural assets as more and more cultural items go through the process of digitisation (Mensink and Van Gemert, 2014).

3.7 Europeana

The Europeana dataset is a large and heterogeneous dataset of digitalised cultural objects taken from the collections of European institutions. With over 50 million objects ranging from 3D images, newspaper and books, photographs and artwork, and artefacts and audio clips, it is one of the biggest digital archives of European cultural heritage. The data are organised in a way that enables further analysis and data visualisation, as well as for representations using graphs, which help analyse the end-objects, hesitate, topics, and the historical period. The materials that Europeana provides are grouped by collections where users can find unique sets of images based on the theme, type of images, and so on: fashion photography, medical illustrations, historical paintings and others – it is an ideal resource for both, researchers or creative professionals.

3.8 WGA dataset

The WGA dataset is a culturally enriched digital archive that has an aspect of an online museum as well as an index of European art. It comprises a database of 47,300 objects of which 11,600 are the digital images of the paintings and sculptures of varied historical periods, gothic, renaissance, baroque and more. Not only do these periods highlight art styles of the periods but also include all the metadata of each of the pieces, as well as information on the artists who were involved, styles, time periods, and dates. The consistencies of its structure and its searchable fields provide users with access to its themes, techniques, and biographies of artists making it a significant architectural tool in art history and digital humanities analysis (Web Gallery of Art, 2024).

Figure 4 Sample images from datasets (see online version for colours)

Table 3 Comparative analysis of available datasets on cultural heritage

Datasets	*Ref.*	*Availability*	*Types*	*Number of objects*	*Object type*	*Description*
OmniArt	ResearchGate (2024l)	Public	Standard	2 million	Image	Yes
WikiArtPaintings	Karayev et al. (2014)	Public	Standard	85,000	Image	Yes
BAM	Xie et al. (2017)	Public	Standard	2.5 million	Image	Yes
IconArt	Gonthier et al. (2019)	Public	Standard	5,959	Image	Yes
PrintArt	Carneiro et al. (2012)	Private	Standard	988	Image	Yes
Rijksmuseum	Mensink and Van Gemert (2014)	Public	Standard	3,593	Image	Yes
Europeana	https://pro.europeana.eu/page/datasets	Public	Graph	50 million	3D images, videos	Yes
Web Gallery of Art	https://www.wga.hu/	Public	Database	47,300	Images	No

4 Performance evaluation measures

Performance evaluation measures (PEMs), to determine the effectiveness or the reliability of the ML and DL models. They assist in determining the efficiency of the model outcome in terms of the assessments of accuracy, preciseness, revelation rate, F1 measurement, area under the curve of precision-recall comparative graph, and Matthews correlation coefficient graph. Table 4 defines the computation of all measures with detail. Accuracy gives the proportion of right guesses over the total number of predictions, while precision and recall target the concern and inclusiveness of positive predictions correspondingly. The F1-score combines precision and recall making it more suitable for datasets where the classes are imbalanced in this case for binary classification. AUC-ROC applies the measures of the extent of the differentiation across the various classification boundaries, while MCC is a highly reliable measure for the evaluations of binary classifier irrespective of the scenario of balance in classes. Altogether, these measures offer the proper strategy of the comparison of the strengths and weaknesses of the models and allow researchers to refine and improve their models if needed.

Table 4 Description of performance measures

Metrics	*Equation*	*Description*
Accuracy	$\frac{TP+TN}{TF+FN+FP+TP}$	Proportion of correctly predicted instances to the total instances in the dataset.
Precision	$\frac{TP}{TP+FP}$	Proportion of correctly predicted positive instances out of all instances predicted as positive.
Recall	$\frac{TP}{TP+FN}$	Proportion of correctly identified positive instances out of all actual positive instances.
F1-score	$\frac{2(precision * recall)}{precision + recall}$	Harmonic mean of precision and recall, useful for imbalanced datasets.
ROC-FPR	$\frac{FP}{FP+TN}$	Proportion of actual negative instances incorrectly classified as positive.
AUC	$\int_0^1 TPR(FPR)d(FPR)$	Measures the model's ability to distinguish between classes.

5 Applications of AI in cultural heritage research

In this section, discuss some application of AI, ML and DL in cultural heritage. Uses of cultural heritage extend across the four areas based on its historical and social/emotional appeal and worth in the economy. This technology has provided broader ground for its application with the help of modern technologies in preservation, tourism, educational sectors, and researchers, as shown in Figure 5.

5.1 Knowledge and perception

Culture gives knowledge and preserves history, history, and art, as well as learning about human civilisations is possible with the help of AI technologies designed to translate texts from ancient languages and scripts (Zhang et al., 2022b). The use of AI can help to provide information about the cultural heritage to the students and common people in general using the latest technologies.

5.2 Digital heritage and accessibility

Cultural heritage is more present now than in the past due to some technology so people across the world can experience it. Virtual digitised collections and virtual museums are available for viewing at any one time as well as any place in the world. Various digital applications include online museum, digital preservation d cultural heritage platforms (Li, 2021).

5.3 Global vision and cultural diplomacy

Heritage acts as a means for cooperation and mutual understanding between nations of the world. Heritage is a way to promote inter-state relationship and understanding. Most cultural heritage resources are now available to audiences everywhere through databases, online museums, and virtual visits (Zhang et al., 2022b). This will help the global community to have virtual visits to online museums and reaching to far a greater number of people from all the globes.

5.4 Cultural heritage preservation and protection

Certain recent technologies help to preserve cultural assets from dangers such as natural disasters, urbanisation, and wars; AI algorithms estimate the effect of various climatic conditions on historical and cultural monuments and suggest actions in advance (Ramtohul and Khedo, 2024). As shared earlier, blockchain can be used for this purpose which is decentralised digital technology which securely records and maintains data ensuring transparency and immutability. The use of this latest technology is being carried out in various fields, including finance, supply chain, and healthcare and CH data preservation is not an exception.

5.5 Analysis and exploration of heritage data

The data analytics techniques are being used worldwide for getting deep insights into the diverse types of data. The three types of data analytics, i.e., descriptive analysis, prescriptive analysis and predictive analytics can be used for optimal analysis of the CH data. AI-based tools make effective analysis of CH data more profound and reveal information previously unavailable. The ML models show the temporal patterns of art, architecture, trade and Decoding Ancient Scripts (Ramtohul and Khedo, 2024).

5.6 Tourism and economic

Cultural heritage is one of the most important aspects while considering tourism globally and example of Egypt thanks to Pyramid is a prime example in this regard. Promoting tourism results in better economic condition of a nation. Marketing of tourism for the Development of local economies and exporting of cultural goods and services. Second also as encouraging cultural entrepreneurship (Song et al., 2024).

5.7 Experiences involving augmented and virtual reality

In Virtual Museums or on Web 2.0 platform the recommended system brings in compelling Virtual reality experiences to the visitors more engaging the return on educations. Interactive application of AR that guides the visitors to go to related objects or history in his physical environment. By enabling immersive experiences for users to explore historical sites and artefacts. Virtual reconstructions of destroyed or inaccessible monuments offer a new dimension to public engagement and education. By combining AI with geographic information systems (GIS), researchers have developed sophisticated models to map historical landscapes and simulate their evolution over time. These applications not only enhance the preservation of cultural heritage but also foster a deeper understanding of its context and significance (Li, 2021).

5.8 Recommendation systems

The recommendation systems are one of the most widely used applications of AI. The recommender systems are used based on two types: collaborative filtering and content-based filtering. Both these techniques have applications in cultural heritage as travel and guide are used world and these can be applied for CH place recommendations. The recommendation system engages communities by providing tips on possible heritage-related activities, volunteering, or projects, and applications where users write or translate relevant content (Li, 2021).

5.9 Online museums and virtual tourism

AI-based platforms supply users with digital immersion for accessing cultural heritage sites remotely across worldwide audiences. AR and VR technologies serve to boost user interaction with these systems. People can access virtual tours as well as 3D models of museums and historical sites throughout the world through Google Arts & Culture (Seila et al., 2025).

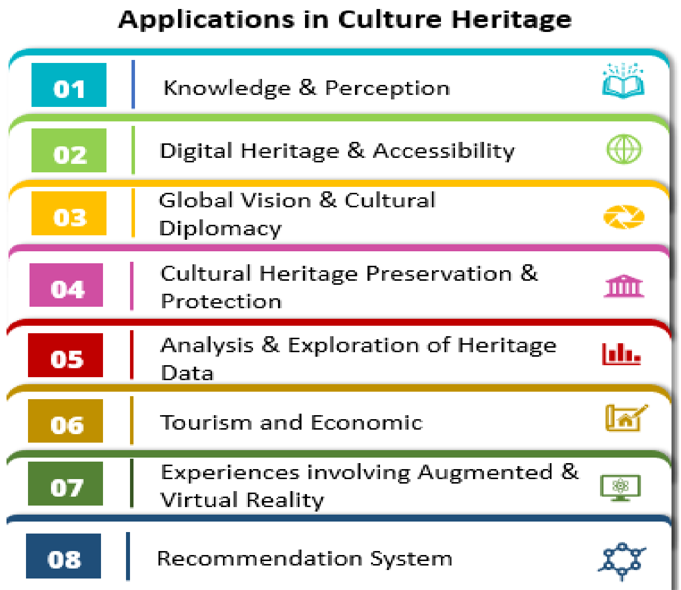
5.10 Protection and risk management

Predictive models assisted by AI technology monitor heritage locations for evaluating possible risks including both natural disasters and climate change and human destruction. UNESCO together with AI experts employ satellite imagery to spot damages inflicted by war on heritage sites (Li et al., 2025).

5.11 Cultural heritage recommender systems

Personalised cultural experiences are provided by AI-powered recommender systems that generate recommendations for historical locations, artwork, and artefacts according to user preferences. AI is used by museums, for example, to suggest exhibitions based on past visitor interests. An AI model provides automatic translation, speech recognition, and instructional resources to help preserve and revitalise endangered languages (Zhang et al., 2025a).

Figure 5 Applications of AI in culture heritage (see online version for colours)



6 Open research challenges and future research directions

In this section, some open research challenges discussed by integrated approaches including ethical concerns, and technology development for these tasks and accomplishing the potential of cultural heritage. The integration of AI into cultural heritage research and practice is not without its challenges. Issues such as data bias, ethical concerns, and the need for interdisciplinary collaboration often complicate the application of AI in this domain, also illustrated in Figure 6. Additionally, the quality and availability of historical datasets remain critical barriers to effective AI implementation. Addressing these challenges requires concerted efforts from technologists, historians, archaeologists, and policymakers to develop robust frameworks and guidelines for AI usage in cultural heritage.

6.1 Data availability and quality

In their former deliberation the performance of ML and DL models was discussed showing the importance of big dataset quality. In cultural heritage, the data acquisition of labelled samples is difficult as objects, manuscripts or inscriptions are rare, scarce and subtly dispersed. Besides, many types of historical data are noisy, contain missing values or are represented with low resolution, which can pose a problem for an AI model to learn (Harrison et al., 2020).

6.2 Inaccuracies in automated restoration and reconstruction

Generally, applying AI in automated restoration and reconstruction, where an object has been destroyed or a building needs reconstruction, involves some elements of approximations that distort the original artefact. However, the use of AI in restoration raises the issue that the details generated for reconstruction may not represent the history and culture, which will thereafter mislead future generations of researchers and society (Fattah et al., 2020).

6.3 Resistance to AI adoption in heritage institutions

AI technologies have not been widely adopted in many heritage institutions including museums, archives and libraries because of perceived costs, lack of skills and resulting in fear of displacement of existing schist methods. Addressing resistance to information technology and specifically AI can be achieved by providing information about the usefulness of the technology, orienting heritage professionals and showcasing AI in practice for heritage management (Pisoni et al., 2021).

6.4 Lack of cross-disciplinary collaboration

It was found that cultural heritage research benefits from the integration of AI but work from this field needs contributions from the fields of computer science, archaeology, art history, linguistics, and ethical issues. However, such collaboration is frequently constrained due to distinct vocabularies, frameworks, or approaches and differing research agendas (ResearchGate, 2024a).

6.5 Integration of multimodal data

In the current study, data mainly concerned with image data were mainly looked at in relation to their classification. Further studies could examine the use of the multiple types of data: textual descriptions, audio, and video, to give subjective perception of the objects in question. This could improve the object classification performances, and they could also have more contextual information about the objects (Song et al., 2024).

6.6 Opportunity for virtual experiences

The people from all over the world cannot come to visit certain cultural heritage locations and museums. AI can be integrated with the latest technologies such as augmented reality and virtual reality. It will help the users at global level to have a virtual tour of the museums and cultural locations. AI based content in images and videos are being generated and similarly, walk-in tour using AI tools can be created for various top cultural locations such as Great Wall of China, Egyptian Pyramid, etc.

Figure 6 Challenges regarding AI in culture heritage (see online version for colours)

6.7 Real-time classification

Real-time classification of the heritage objects using DL models requires technical work where heritage objects can be put in different settings such as museums or archaeological sites. The implications of the results for AI research could include investigating how model size, particularly when pre-trained models with millions of parameters are used, may be reduced while keeping inference-time loss accurate enough to meet demands in dynamic environments (Çöltekin et al., 2020).

6.8 Cross-cultural collaboration and data sharing

A challenge exists because cultural institutions together with researchers and governments struggle to collaborate because of data ownership disputes and restrictive policies that prevent mutual information sharing. International collaborations utilising AI heritage management should be created through the development of frameworks which include transparent data exchange agreements (Jiang et al., 2025).

6.9 AI explain ability and trustworthiness

The black-box nature of AI models used in cultural heritage creates an essential barrier because historians and researchers find it hard to depend on results which are not transparent. AI models should integrate XAI features to present understandable explanations along with justifications for the cultural heritage analysis produced by AI systems (Zhang et al., 2025b).

6.10 Security and protection against digital threats

Digital archives incorporating content made by AI face threats from cyber-attacks along with unauthorised changes and deepfake distortions which require AI security systems for threat detection and prevention (Candela, 2025).

This gap could hamper the growth of an overall AI system capable of solving all the issues in cultural heritage conservation. All these challenges give credence to the continuous effort in the pursuit of accurate classificatory models of heritage objects via DL methodologies.

7 Conclusions

Cultural heritage is a means by which people can maintain the link and continuity with the past through impacting current personalities as well as form the character of the generations to come. AI, ML and DL based technologies have emerged as an innovative change agent in terms of conservation, understanding, and sharing of cultural assets. This study aims to present systematic literature review of the emerging and promising domain of AI, ML, and DL in cultural heritage. A detailed examination of applications discusses and additionally presents different dataset that used in this field. This review also showed how these technologies are changing the landscape of heritage practice through providing advances in digitisation, restoration, education and individualised engagement with cultural artefacts. The review is divided into ML and DL techniques exploring diverse model-based approaches for the applications in CH. The study reveals that CNN model and diverse pre-trained models based on CNN architectures are being widely used in the relevant studies.

To be able to develop further and yet keep the value of cultural heritage intact, the field must encourage interdisciplinary collaboration, discuss Open research challenges and furthermore discuss future direction to an analysis of research trends for using AI in cultural heritage.

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Declarations

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