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AI for Heritage Preservation: Multi-Class Image Classification of Indian Temple Iconography

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Abstract:

This study proposes classifying Hindu deities based on their distinct iconography with a multi-class recognition. A curated dataset of 500 high-resolution images from Ajanta, Ellora, and Hoysala temples was organized into three iconographic categories: Meditating Buddha, Dancing Shiva (Nataraja), and Other Sculptures. ResNet50 and EfficientNet architectures were used to train the models to distinguish the visual features including hand gestures (mudras), postures, and deity-specific artefacts. The best-performing model achieved 92% overall accuracy and was strong in identifying Meditating Buddha and Dancing Shiva, and errors occurred when distinguishing Standing Buddha and Other Sculptures. This approach demonstrates how large-scale digital archives can be developed with the aid of machine learning. With majority of the images classified by the machine in the archive, scholars can utilise their time to understand minute nuances and draw cultural and theological conclusions which is a valuable step in heritage preservation.

Keywords: *Digital archive; Multi-class classification; Computer Vision; Transfer Learning; Iconography; Indian Temple Sculpture; Heritage Preservation;*

Introduction

In Indian temples sculptures tell stories of cultural and religious significance through nuanced symbolism. These visuals of Buddhist, Hindu, and Jain traditions help understand Indian art and philosophy. However the diversity and other stylistic variations in sculptural iconography [1] is challenging for scholars to manually categorize and interpret. This is mainly because of two reasons : damage to sculptures and the time it takes for manual classification. Traditional studies tend to emphasize text interpretation or small-scale case analyses, which are not well-suited for large sets of visual data [3].

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The detailed study of these sculptures is essential to understand medieval India [2 and in heritage preservation, especially since these ancient sculptures undergo wear and tear and lose the stories and myths they represent over time.

Recent advances in computer vision and deep learning help immensely to automate the study of temple sculptures. Computer vision can be trained to classify deities based on their features like postures, companion deities, and artefacts with useful metadata. There is much scholarly material on Indian temples [19][20], however this research has not reflected in visual media. It is essential to integrate such research into digital archives to enhance preservation efforts of Indian cultural heritage [21]. Along with studying temples in person, gaining knowledge from local experts for understanding the local histories [4], incorporating digital technologies will help advance iconographic research.

This study applies transfer learning models namely ResNet and EfficientNet to classify temple sculptures into three categories: Meditating Buddha, Dancing Shiva, and Others. The results of this study demonstrate the AI-driven digital archives definitely help scholarly research.

The paper is organized as follows. The literature review sheds light on digital preservation techniques used world-wide for preserving heritage and also show that digital technologies have not been used for iconographic studies. Next, the methodology section shows how transfer learning models are used in the study and the results of the study that include the performance metrics. The discussion section debates the merits and demerits of multi-class image recognition in digital archives. The conclusion highlights how a AI-powered framework is helpful for both scholars and the general public to understand India’s rich architectural traditions.

Literature Review

Digital preservation of the heritage has been addressed from various viewpoints, from architectural documentation to computational processing and digital humanities. This section outlines main research strands pertinent to cultural heritage and iconographic studies.

1. Architectural Preservation

Researchers have focussed on extensively documenting and preserving the physical elements of monuments. A computer-driven model [5] assesses the resilience of heritage buildings for heritage upkeep. [10] uses photogrammetry and 3D data acquisition showing how digital documentation can help revive damaged structures. [11] uses China's built heritage for construct knowledge visualization.

2. Informal Archives

Digital humanities save cultural memory with the help of software. For example this study [6] uses suffrage postcards to identify gender-wise participation and another research investigates colonial cemeteries with digital technologies. There many informal archives such as in [9] which analysed the community records of India. [17] developed extensive platforms to archive Singaporean Chinese cultural heritage with the help of WebGIS.

3. Use of Machine Learning and AI in Cultural Heritage

Recent studies use AI analyse art. Artefact classification, restoration, and conservation efforts are increasingly utilising AI [8]. In [13] sculptures of Lord Shiva Linga and Ganesha are classified deep learning. Raphael's paintings [15] were analysed with SVM with 98% accuracy in another. These examples show scholarly research can be augmented with AI and deep learning.

4. Iconography and Symbolism in Indian Temples

Temple iconography studies show the richness of the visual and symbolic art in Hindu temples. In a study [12] the researchers deconstruct Hindu temple architecture proving the cultural continuity in the temple art. Another research [14] focussed on tribal origins of Odisha temples, showing impact on architectural and sculptural themes. [16] shows the regional diversity and philosophical bent in the temple architectures from north and the southern India. The following table illustrates some of the previous literature associated with the digital preservation efforts for historical.

Table 1: Summary of existing research work

Authors with year	Key points of work	Findings
[5]	Proposes using a computer-generated representation of structural and artistic elements to evaluate heritage building resilience.	Offers insights into combining static and dynamic information for the maintenance and safety of ancient buildings.
[6]	Utilizes digital humanities to investigate suffrage postcards and feminist digital humanities.	Explores the role of gender markers in designing postcards and provides new views on the early twentieth-century suffrage movement through data visualization techniques.
[7]	Investigates the colonial cemetery as an archive using digital humanities tools.	Reveals previously neglected connections and unburns the company's history through advanced search algorithms and software.
[8]	The study focusses on the application of machine learning techniques to cultural heritage, including image analysis, object	Identifies key areas where machine learning has been successfully applied in cultural heritage, including artifact classification,

	recognition, and data interpretation.	restoration, and digital preservation.
Authors and title	Short abstract	Findings
[9]	Examines informal archives in Indian communities through empirical studies and ethnographic methods.	Highlights the significance of unofficial records in understanding historical events and national remembrance.
[10]	Utilizes photogrammetry and long-range laser scanning for 3D data capture in architectural surveys.	Demonstrates how digital documentation can help preserve heritage buildings even if partially collapsed.
[11]	Develops a technique called digital preservation and utilization based on knowledge visualization (DPUKV) to preserve architectural history.	Confirms the methodology's suitability for various cultural heritage sites through case studies on China's architectural legacy.
[12]	The study proposes a framework for analysing the Indian temple art. Research utilizes visual and graphical analysis techniques alongside an extensive literature review to interpret and classify Hindu temple architecture.	Identifies various visual and theoretical frameworks for interpreting temple architecture. Highlights inconsistencies in dimensional accuracy and potential misinterpretations in past research. Emphasizes cultural continuity and symbolism in temple designs.
[13]	The methodology used in this research involved acquiring images of Indian sculptures, preprocessing them by resizing and converting to grayscale, and classifying them using a CNN-Sequential model with activation functions such as ReLU, Sigmoid, and Binary Crossentropy.	The findings of this research indicate that a CNN model was successfully implemented to classify images of Lord Shiva Linga and Lord Ganesha with a high accuracy of 91%. The research highlights the effectiveness of deep learning and convolutional

		neural networks in image classification tasks.
[14]	This study conducted an investigation of constructed forms, structures, ornamentation, and themes. It also examined the tribal origins of numerous deities. Data for this study was acquired through temple visits, expert interviews, and published material. The study aimed to establish a connection between tribal art and temple architecture in Odisha.	Reveals how tribal architecture has influenced the temples in Odisha. Highlights the evolution from thatched structures to detailed stone temples. Shows how these the visual elements from tribal art has influenced structures such as Jagamohan, Natamandap, and Bhoga Mandap. Documents the use of tribal motifs and patterns in temple carvings.

Research Gap

Most of the existing work use technology for heritage preservation, cultural studies, and the analysis of historical artefacts. But there is hardly any research that focusses on the iconographic study of Indian temple sculptures. While studies like [8] and [12] try to utilise machine learning for heritage and temple architecture, they do not adequately address the complexities of Indian temple iconography. The focal point of most studies is the physical preservation of monuments than in understanding the symbolism and cultural impact.

Some studies like [5] and [10] use digital tools for preserving heritage sites through documentation, but their studies do not include iconographic elements. On the other hand, studies like [12] identify inconsistencies in past research on temple architecture, but they do not assimilate technology to classify or recognise iconography.

Thus, combining traditional wisdom, scholarly research with digital technologies such as computer vision, image recognition algorithms, and natural language processing to understand and research the iconography of Indian temples will immensely enhance the progress made towards preserving them. This study aims to go beyond mere classification and include scholars in the loop for adding meaning, cultural nuances, symbolism into digital archives. This will effectively bridge the gap between theological and historical studies and computing technologies.

Methodology

This study shows how well an image recognition engine can help classify deities based on their distinct features. While expert scholars might be able to perform this task using the technology saves their valuable time to research the details. For the inexperienced heritage enthusiasts, the machine classification will help understand the sculptural nuances at least broadly, if not perfectly.

Dataset Description

The study uses a dataset curated that captures the diversity of Indian temple sculptures that span religions and different ionographic traditions. It is hard to obtain datasets for a study that requires very specific images. Hence it was important to curate a good dataset though small. Public archives, generous donations from freelance photographers, and personal albums formed the basis of the dataset used in this study. Photographs are from Buddhist sites such as Ajanta and Ellora, Shivite temples such as the Hoysalas from the southern India. The dataset consists of 300 high-resolution images that are annotated and segregated into three categories., namely Meditating Buddha, Dancing Shiva (Nataraja), and Other Sculptures. Each category has approximately 100 images to for a good balance and reliable training.

To fit the requirements of deep learning models, images were resized to 224 × 224 pixels and normalized to achieve consistency in scale and lighting. Data augmentation techniques were used to increase the dataset for better training. The data augmentation included random rotations, flips, cropping, and also brightness adjustments to expand the dataset and have more variations within each category. While curating the dataset, the training set included distinct iconographic cues such as mudras, postures, symbolic attributes, and attire, those that help identify deities.

Though this is a three-class classification, this can be expanded to any number if there are enough images available for training. Building future digital archives using such a classification will provide a readymade image corpus for researchers. Also, for general public, attractive visual galleries can be built using the classification – which in turn will encourage people contribute to the archive.

Model Training

This study employed deep learning techniques to classify Indian temple sculptures into three iconographic categories: Meditating Buddha, Dancing Shiva, and Other Sculptures. The methodology consisted of curating the dataset, preparing it for training, designing a model, training, and finally testing for accuracy.

The curation involved extensive collection and inspecting them for suitability – if the images showed very unclear images or damaged sculptures or some very generic features – they were eliminated. To balance the quality, along with images of temple sculptures some high resolution photographs were also included. The 500 images were then resized to 224 × 224 pixels, normalized, and augmented with rotation, cropping, and brightness adjustment. This

gave a dataset that had enough variation, precision when it came to training, uniform lighting and size so that model training was consistent.

The methodology included using two different transfer learning architecture – one is ResNet50 and the other EfficientNetB3. Both are pretrained models trained on ImageNet. These models were fine-tuned with the curated dataset to achieve multi-class classification. Here the final layers were modified to accommodate three categories. Adam optimizer with a learning rate 0.0001 was used with a batch size of 32 in 30 epochs. Early stopping was employed to avoid overfitting.

Performance was assessed using accuracy, precision, recall, and F1-score, with a confusion matrix for error analysis. Heatmaps and Grad-CAM visualizations brought to notice the elements of each sculpture that influenced classification, which further helped curate datasets and also perform valid reasoning with explainable AI.

Experimental Results

The 300 photos in three categories those of Meditating Buddha, Dancing Shiva, and Other Sculptures, were used to train the deep learning models. By retaining ImageNet pre-trained weights adjusted and fine tuning with the custom dataset, transfer learning was used to create both ResNet50 and EfficientNetB3. To evaluate the model's performance the study considered both per-class accuracy and total accuracy.

Total Performance

As shown in Table 1, EfficientNetB3 surpassed ResNet50 with an overall accuracy of 93%, whereas ResNet50 reached 90%. The findings show that even with a little sample, transfer learning enables efficient iconographic category detection. Also, EfficientNetB3 is better at finding more details for classification than ResNet50. While ResNet50 is a strong architecture, EfficientNetB3 is more efficient given its efficient design. The reason behind the improved accuracy by EfficientNetB3 can be attributed to its capability in extracting details and that it is pretrained on a larger class of images. While both models are shown to perform well on large datasets, on small datasets EfficientNetB3 performs better.

Performance by Class

Meditating Buddha (Fig 2) and Dancing Shiva or Nataraja (Figure 2) achieved the best accuracy. Photographs of meditating Buddha were identified by EfficientNetB3 with 96% accuracy, whereas photographs of dancing Shiva were classified with 95% accuracy. What might have helped the accuracy here are the unique iconographic characteristics of these categories – Shiva in his Nataraja or the dancing form has his leg raised and crossed and also sports numerous arms. Meditating Buddha sits in a unique posture with the hands folded characteristically in what is called the Dhyana Mudra. Also since images of meditating Buddha has him in a seated position could have resulted in the higher degree of accuracy in classification.

These two categories also showed good precision scores (95% for Buddha and 94% for Shiva), in addition to the best accuracy. This suggests that the model not only properly classified these sculptures but also generated fewer false positives when making predictions about them. These results exhibit that model is dependable when presented with images where the features are strongly recognisable. Hence, it is safe to categorise the ones which exhibit high precision and accuracy in the archives and leaving only the erroneously recognised ones for human classification.

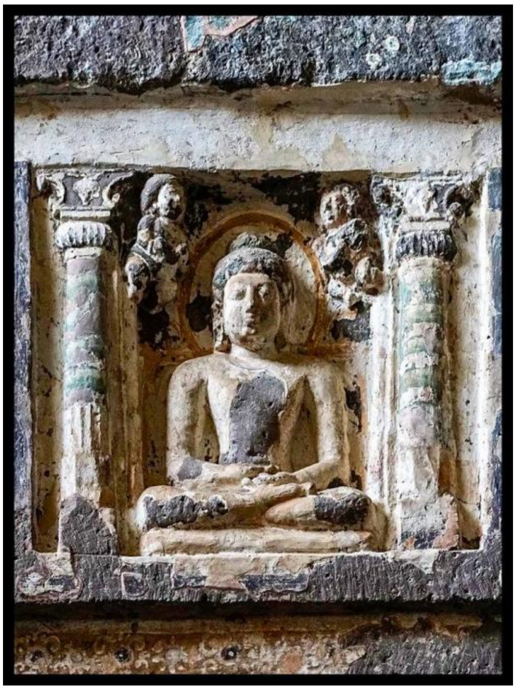

Fig. 1, Buddha in meditative stance

Fig. 2, Dancing Shiva or Nataraja

The category that contained images of other sculptures, classified as Other Sculptures, achieved low accuracies of 88% with EfficientNetB3 and 84% with ResNet50. This category also showed low precisions of 82 and 86 percentages respectively. This category contained a very heterogeneous mix of images including that of dancers, panels depicting mythological stories, other deities such as Shakthi and Krishna, and mythological figures – and they all exhibited diverse attributes. This broad variation confused the model and led to led to occasional misclassifications. For example, many figures with upright postures got wrongly classified as Shiva and those in sitting postures got classified as Buddha. Also the cases where the images contained eroded symbol, they got misclassified. This shows that in the multi-class classification, there is a need for every class to exhibit distinct features rather than an assortment of features. The model will fail to understand highly varied features.

FINDINGS AND DISCUSSIONS

The experimental findings show that it is both possible and efficient to classify Indian temple sculptures into multiple classes, even if the dataset is not large. As the results show, Meditating Buddha and Dancing Shiva (Nataraja) had the greatest accuracy and precision ratings out of the three categories considered. The more uniquely identifiable the iconographic characteristics, the better are the outcomes. The model is able to recognise the folded hands, a feature that provides a clear visual cue for identification coupled with the seated position. However, in the others category, most seated sculptures were wrongly classified as Buddha.

The Dancing Shiva has features that the model was able to recognise - a raised and crossed leg, and many arms, which are recognizable visual cues. Again, many upright sculptures with multiple hands the others category were misclassified as Nataraja. This clearly shows that models require categories where the features are not overlapping and with fewer distinguishable characteristics.

Table 1: Class-wise Accuracy and Precision of Models (Three Categories)

Class	Metrics	ResNet50 (%)	EfficientNetB3 (%)
Meditating Buddha	Accuracy	94	96
Meditating Buddha	Precision	93	95
Dancing Shiva	Accuracy	92	95
Dancing Shiva	Precision	91	94
Other Sculptures	Accuracy	84	88
Other Sculptures	Precision	82	86
Overall	Accuracy	90	93
Overall	Precision	89	92

The Class Precision Comparison as shown in Figure 3, reveals EfficientNetB3 consistently scores higher precision than ResNet50 for every sculpture category. The biggest jump is in Other Sculptures (+4%), suggesting EfficientNetB3 eliminates spurious positives and classifies minority/complex classes better.

EfficientNetB3 proves to be a better performer than ResNet50 in terms of both accuracy and precision. The improvement is highest with the "Other Sculptures" class, where EfficientNetB3 tends to generalize better. Generally, EfficientNetB3 improves by about three percentage points in terms of accuracy (93% compared to 90%) and precision (92% compared to 89%), making it the superior and more reliable model for this classification task.

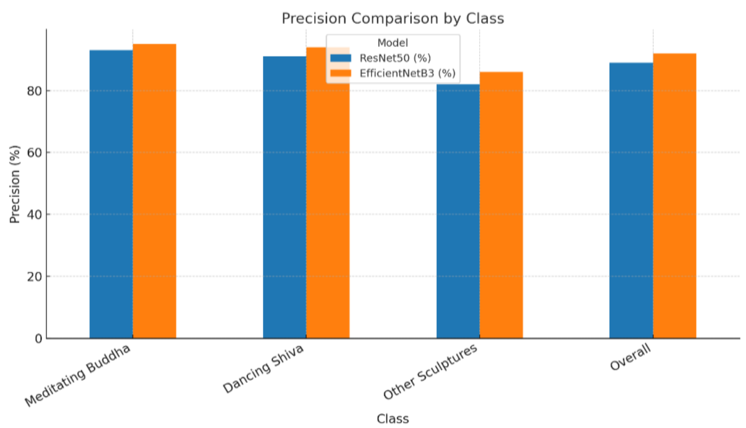

Fig 3 : Precision Comparison across Models

Further Research

This study is not limited to a few multi-class classification problems but a gateway to new and exciting further research. However, the most important facet is to curate datasets of varied deities even if the dataset size is small. The model learns better when trained with multiple categories of deities with distinctive features and from across different regions of India. This diversity will help in categorising images automatically in the archive for easy and systematic storage and retrieval. Also including sculptures in varied conditions such as eroded, damaged, or even stylistically different. Mixing these with images of paintings or artwork will help the model learn the features and will fare better even when posed with blurry featured images. Scholars and technologists working together with art collectors, museums, and archaeological archives will help build the dataset.

Further, mimicking how researchers work, models can be trained to recognise hierarchies rather than flat classifications. For example, models can first recognise and classify sculptures as standing, sitting, or dancing postures before moving on to predict the deity. Such a classification would misclassifications when the features overlap. In the above study, a sculpture can be simply classified as dancing rather than wrongly predicting it as Nataraja with such hierarchical classification.

Third, using attribute-based classification will be complex but it will enhance accuracy and interpretability. To identify a deity, its characteristics such as posture, number of arms, artefacts the deity is holding can be recognised separately and then merged. This will help enrich the archives with detailed metadata as well.

Using multi-modal approaches where scholarly texts, texts extracted from inscriptions, temple records, or even from current-day research alongside the images is an exciting prospect. Further to this, small language models will help retrieve images and the related texts aiding the researchers. This is possible by using models such as CLIP, which align text and images.

Conclusion

This study shows how deep learning and transfer learning may be used to classify Indian temple sculptures into multiple classes. The results of the experiment show that AI can provide dependable classification when the training is done on distinguishable features. Once basic classification is taken care of, researchers can focus to more complex topics where the human scholarship is required. For example, only scholars can determine what cultural and religious backgrounds influenced the artistic traditions.

Another important application of this research is in heritage preservation. Models can be trained to flag sculptures that are damaged and need repair. Conservators can use the help of technology to routinely identify sculptures that need restoration.

Finally, the study clearly can act as a valuable educational resource. A metadata-enriched image with visual markers of salient features, helps visitors, students, and heritage enthusiasts to understand the iconography and engage more deeply with temple art. This fosters curiosity, cultural pride, and a stronger preservation instinct among public.

In conclusion, the research that leveraging digital technologies will advance the analysis and interpretation of Indian temple iconography. Image recognition and natural language processing incorporated into digital archives will provide a ready understanding of symbolic meanings of temple sculptures. The proposed study exhibits the practical application of modern technologies to understand and preserve India's rich cultural heritage.

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