3DITA – A 3D Benchmark Dataset for Nagara-Style Indian Temple Architecture: India's First Point Cloud Dataset for Semantic Segmentation

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Abstract

The rapid advancement of deep learning (DL) methods for point cloud processing has significantly increased the demand for large, diverse, and annotated datasets to improve model performance across various applications. In the cultural heritage domain, the availability of such datasets is crucial for driving innovation in algorithm development. However, a notable gap exists due to the limited availability of large-scale, labelled point cloud datasets specific to heritage structures especially within the Indian context. This study introduces 3DITA—the 3D Indian Temple Architecture Dataset—India's first benchmark point cloud dataset tailored for semantic segmentation of Nagara-style temple architecture. The dataset comprises over 325 million points, captured from 47 temple structures using Close-Range Photogrammetry (CRP) and Terrestrial Laser Scanning (TLS). A total of 22,370 photographs were used to reconstruct 46 temples via CRP, while TLS was employed for one site, ensuring high-resolution and geometrically rich data.
To evaluate the dataset, a deep learning-based segmentation framework was implemented using PointNet and DGCNN architectures. The models were trained to segment culturally specific classes including Walls, Mandapa, Shikhara, Amalaka, and Garbhagriha. The DGCNN model achieved a peak accuracy of 80%, outperforming the PointNet and demonstrating the dataset's robustness in handling the geometric complexity of Indian heritage structures. Beyond semantic segmentation, 3DITA serves as a foundational resource for a range of applications, including heritage reconstruction, digital twin development, Historic Building Information (HBIM) modelling, and large-scale heritage preservation. By making the dataset available upon request, this study aims to support future research and foster interdisciplinary collaboration in AI-driven cultural heritage documentation and analysis.

1. Introduction

India, being one of the richest sources of tangible heritage on the globe, has a mind-boggling collection of monuments, archaeological sites, and ancient artifacts that span from prehistoric settlement to colonial-era architecture (Kumar, Meena and Patiyal, 2025). Despite the richness of this heritage, documentation efforts remain fragmented. National bodies such as the Archaeological Survey of India (ASI), State Archaeology Departments, and INTACH (Indian National Trust for Art and Cultural Heritage) have been instrumental in preserving and recording parts of India's cultural assets. However, large portions of this vast heritage remain undocumented or poorly archived, largely due to the massive scale, dispersed nature, and structural complexity of these monuments. Moreover, the absence of a unified digital database further complicates efforts in heritage conservation, research, and management (Kumar, Meena and Patiyal, 2025). Given the challenges posed by time, climate, and modern development pressures, it is essential to adopt both traditional conservation practices and technological approaches such as 3D documentation to ensure their survival for future generations (Bassin, 2024; Varghese, 2024).

In this context, digital technologies have emerged as powerful tools for documenting cultural heritage. Point cloud data obtained from Close Range Photogrammetry (CRP) and Terrestrial Laser Scanning (TLS) provides both geometric and radiometric information useful for heritage documentation and analysis (Zhao *et al.*, 2024). Radiometric information refers to non-spatial attributes of the scanned surfaces, specifically the light reflectance properties that help in material identification and surface characterization (Sánchez-Aparicio *et al.*, 2018). Geometric information includes features such as surface normals, which can be used to detect deformations, material losses, and structural irregularities (Sánchez-Aparicio *et al.*, 2018). However, geometric attributes are not directly available in raw point cloud data; instead, they must be derived through interpretation and processing. Semantic segmentation of heritage point cloud enhances virtual 3D reconstruction by embedding contextual meaning into the geometry of cultural heritage elements (Yang, Hou and Li, 2023). Semantic segmentation is essential for historical architecture since it enables the automatic identification of individual architectural elements. Automation significantly minimizes the workload and speeds up analysing in-situ point clouds and building parametric 3D models (Pierdicca *et al.*, 2020; Lovell, Davies and Hunt, 2023). It is especially important for high-level documentation, conservation design, and lifecycle management of heritage buildings (Guo *et al.*, 2024).

However, automatic point cloud segmentation remains a subjective and complex task (Griffiths and Boehm, 2019). It needs architectural knowledge, patience, and detail considerations that restrict its scalability and are responsible for the absence of annotated datasets. Manual segmentation, though trustworthy, is much too time-consuming and labour-intensive for large scale heritage documentation (Basu *et al.*, 2023). While deep learning-based semantic segmentation has been promising results in terms of accuracy, their use on cultural heritage sites in India is limited because of lack of large-scale, annotated datasets encompassing specifically Indian architecture (Griffiths and Boehm, 2019; Zhao *et al.*, 2023). These concerns illustrate the imperative need for tailored semantic segmentation techniques and the development of relevant datasets to enable more automation, accuracy, and efficiency in HBIM processes specific to the Indian heritage context.

The study bridges this gap by creating a benchmark point cloud dataset specifically for the semantic segmentation of Nagara-style Indian temple architecture. It addresses the lack of detailed scans of Nagara temples on a uniform platform, enabling comprehensive and customized applications. The 3DITA dataset is made publicly available upon request, allowing researchers to utilize it for developing and testing various deep learning algorithms. Additionally, this study provides an in-depth comparison between the DGCNN algorithm and the baseline PointNet for deep learning-based point cloud semantic segmentation in HBIM applications. By bridging the gap between AI and cultural heritage, this study contributes to advances in digital reconstruction, HBIM modelling, digital twins, and long-term preservation of culturally significant built environments.

2. Methodology

2.1 Study Area Identification

Indian structures exhibit diverse architectural styles across historical periods, making it challenging to develop a dataset that comprehensively represents the entire country. However, when it comes to temple architecture, Indian temples are primarily classified into three types: Northern style (Nagara), Southern style (Dravida), and Mixed style (Vesara).

Among these, Nagara is the oldest, emerging from the 5th century CE onward. Although it originated in northern India, later spread across the subcontinent. Nagara temples are typically built on high platform and enclosed by a series of concentric walls characterized as Shikhara, Garbhagriha, and Amalaka. The preservation of Nagara temples is not only an act of safeguarding architectural legacy but also of protecting India's spiritual and cultural identity.

For this study, the state of Uttarakhand, India has been selected as the primary region for analysing Nagara-style temple architecture. The geographical spread of the study area, including the various districts of Uttarakhand and selected Nagara-style temple sites are represented in Figure 1.

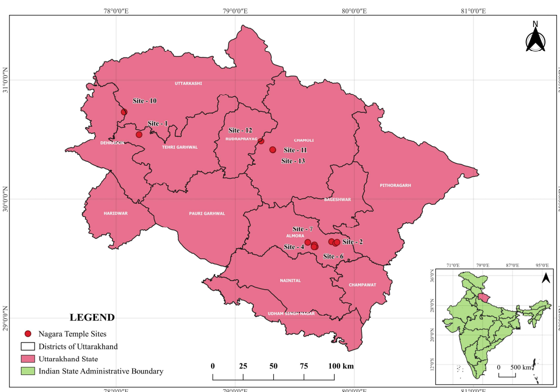


Figure 1. Study area map

In this study, emphasis also placed on documenting such lesser-known, vulnerable temples which are at risk of decay or destruction, thereby underlining their importance for conservation and digital preservation. In the interest of supporting the development of a 3D semantic segmentation dataset, 13 temple locations encompassing 47 temple structures have been selected. Table 1 presents a detailed list of the selected temple sites with number of structures captured.

Table 1. Overview of selected sites for dataset creation

Site Number	Temple	District	Latitude	Longitude	Structures
Site 1	Devalsari Temple	Dehradun	30.54494	78.19254	1
Site 2	Shiva Temple	Almora	29.64258	79.8086	1
Site 3	Tripura Sundari Temple	Almora	29.61428	79.66159	1
Site 4	Chiteeshwar Temple	Almora	29.6007	79.6722	1
Site 5	Dandeshwar Group of Temples	Almora	29.6291	79.842	9
Site 6	Paatel Devi Temple	Almora	29.6158	79.6653	1
Site 7	Katarmal Sun Temple	Almora	29.63701	79.6091	2
Site 8	Jageshwar Group of Temples	Almora	29.63753	79.85483	13
Site 9	Nanda Devi Temple	Almora	29.6001	79.6616	1
Site 10	Lakhamandal Shiv Temple	Dehradun	30.7313	78.0675	3
Site 11	Shri Gopinath Temple	Chamoli	30.4139	79.3161	1
Site 12	Tungnath Temple	Rudraprayag	30.4885	79.2168	6
Site 13	Vaitrani Group of Temples	Chamoli	30.4161	79.3145	7

2.2 Benchmark Dataset Creation

Preparation of the dataset is important in 3D semantic segmentation. Deep learning techniques relies on high-quality data and variability to train the models and generate predictions (Hu *et al.*, 2021). To assess the performance of deep learning models used for the semantic segmentation of point cloud data, having a representative and reliable benchmark dataset is crucial (Zhang *et al.*, 2019). Due to the lack of such datasets in the Indian context, this study has undertaken the development of a dedicated dataset focused on Nagara-style temple architecture, which aims to make a substantial contribution to the field of cultural heritage documentation and support semantic segmentation research. Thus, the dataset for this project has been prepared cautiously to be rich, varied, and representative within the available semantic classes. Figure 2 illustrates the methodological framework followed for the creation of benchmark dataset.

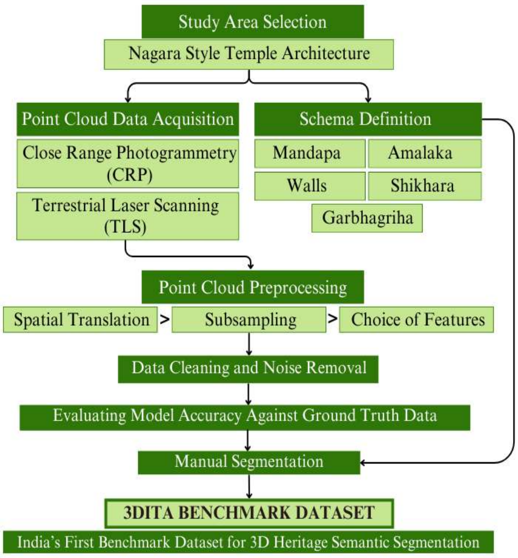


Figure 2. Methodology workflow

2.3 Data Acquisition

In the current study, data were acquired using proximal remote sensing methods, specifically Close-Range Photogrammetry (CRP) and Terrestrial Laser Scanning (TLS). CRP data were collected from 12 study areas, yielding a total of 22,370 images. Additionally, TLS data were acquired from one study area using a FARO Focus 350 scanner, which captured approximately 13 million points.

To document the entire exterior of the selected temple, 15 scans were performed at 3× precision and 1/8 resolution (6.1 mm at 10 m), with each scan taking around 15 minutes. Reflective targets were installed in advance to facilitate scan co-registration. For successful alignment, at least three common targets needed to be visible between any two scan positions. After setting up the tripod and scanner, scanning parameters were configured, and sequential scanning was conducted. The identification of blind spots was a critical factor in determining scanner placement. Given the FARO Focus 350 maximum effective range of 200 meters, maintaining close proximity to the structures was essential.

2.4 Data Processing

Techniques for processing CRP data particularly overlapping images are now well-established, with numerous algorithms capable of automating the complete workflow for generating dense 3D point clouds using Structure-from-Motion (SfM) techniques. Prior to processing, a manual screening of the captured photographs was conducted to eliminate low-quality or irrelevant images, such as blurred, accidentally captured, or improperly angled photos. This quality control step was essential to ensure the accuracy of the reconstructed 3D geometry. The filtered overlapping images were then imported into photogrammetric software to generate point clouds of the temple structures. These point clouds were subsequently exported for further processing. In TLS directly produces point clouds; however, multiple scans from different viewpoints must be co-registered to form a complete and accurate 3D model of each structure.

After generation, point clouds from both CRP and TLS were exported in LAS format to ensure compatibility across software platforms. From this stage onward, both datasets were processed using a unified workflow. Pre-processing steps included spatial translation (for geometric alignment), subsampling (to reduce point density while retaining structural integrity), and computation of features and normals to standardize the data for semantic segmentation and analysis. A spatial subsampling rate of 0.01 was applied in this study, resulting in only a 1% data reduction. This conservative subsampling preserved intricate carvings and geometric details characteristic of temple architecture without compromising dataset quality.

Subsequently, noise removal was performed to eliminate non-structural elements. Since CRP and TLS inherently capture portions of the surrounding environment during data acquisition, extraneous elements were filtered out. This ensured that the resulting point clouds were restricted to the defined semantic classes specific to temple structures. The overall data processing workflow is illustrated in Figure 3.

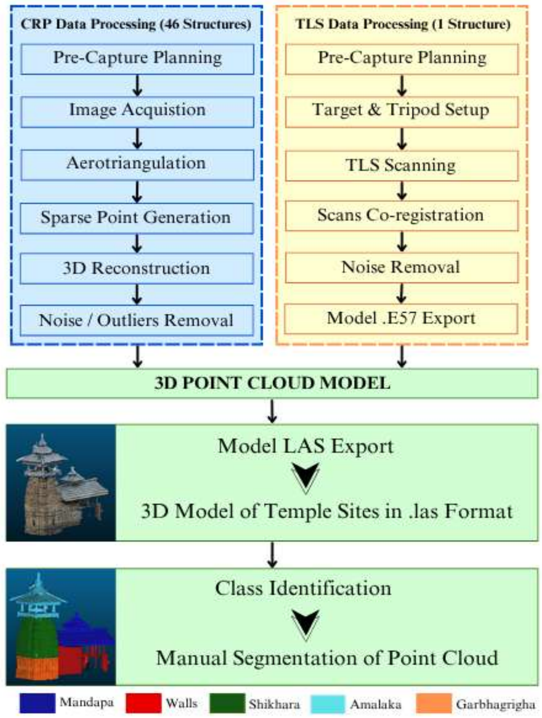


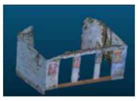
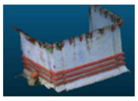
Figure 3. Processing steps of point cloud for dataset creation

2.5 Schema Preparation and Manual Segmentation

Class definitions for semantic segmentation are critical for successful implementation of automatic deep learning-based methods. Manual annotation of the 3D dataset is essential for the creation of a benchmark dataset. Nevertheless, this step cannot be neglected. Compared to typical 3D urban scenes, the annotation of point cloud samples in the cultural heritage domain requires more professional knowledge and domain-specific expertise (Yang et al., 2023). Therefore, careful preparation of the annotation schema is required, which involves identifying appropriate classes for semantic segmentation.

In this study, class selection was guided by field expertise and application requirements in HBIM. As outlined by (Hu *et al.*, 2021), two main criteria were followed in defining the semantic categories: (1) Each category should have a clear semantic meaning that is relevant to social or commercial applications; and (2) Different categories should exhibit distinct geometric structures or visual appearances. Key architectural components garbhagriha, shikhara, mandapa, walls, and the amalaka are defined as semantic classes in the dataset. These elements represent distinct and culturally significant components of Nagara-style temple architecture. Table 2 summarizes each class along with representative images, brief descriptions, and unique visual characteristics that aid in their identification within the point cloud data.

Table 2. Semantic class definition for dataset creation

Category	Image	Description	Distinct Visual Characteristic in Dataset
Mandapa		A pillared hall serves as a transitional space between the outer temple and the inner sanctum.	Usually located at the front of the temple, featuring a roof.
Walls		Structural elements forming the external and internal boundaries of the temple, typically constructed from stone.	Positioned beneath the mandapa or around the garbhagriha.
Shikhara		The prominent curvilinear tower positioned above the garbhagriha.	Directly above the garbhagriha.
Garbhagriha		The innermost sanctum of the temple, literally meaning "womb chamber," where the main deity's idol is enshrined.	It is typically located directly beneath the shikhara.
Amalaka		A circular stone disc, often ribbed and resembling a lotus, it symbolizes spiritual purity and crowns the temple's vertical elevation.	Placed at the apex of the shikhara.

The manual annotation was performed for all the temple 3D structures, where each class label was added as a scalar field. The annotated point clouds were then exported as '.txt' files containing the 3D coordinates for each point. This process was carried out individually for each structure, ensuring consistency in format. The final structure of the processed point cloud data consists of the following attributes: *x, y, z, and label*.

3. Results

This study presents 3DITA (3D Indian Temple Architecture), the first publicly available benchmark dataset, specifically for Indian cultural heritage semantic segmentation, targeting the Nagara temple architectural style. The dataset aims to support the training, validation, and benchmarking of machine learning and deep learning algorithms in the heritage domain. The 3DITA dataset consists of over 325 million manually annotated 3D points, collected using two techniques: Close-Range Photogrammetry (CRP) and Terrestrial Laser Scanning (TLS). A total of 47 temple structures across 13 different study sites were documented. Of these, 46 structures were reconstructed from 22,370 photographs using CRP, yielding a dense point cloud of approximately 312 million points. One structure was captured using TLS, generating an additional 13 million points. Each point in the dataset is manually labelled into five semantic categories relevant to the architectural components of Nagara temples. These classifications are intended to facilitate structured training of deep learning models for heritage-specific applications. A visual overview of the dataset, including its spatial and categorical distribution, is provided in Figure 4. The 3DITA dataset is available upon request for academic and non-commercial research use.

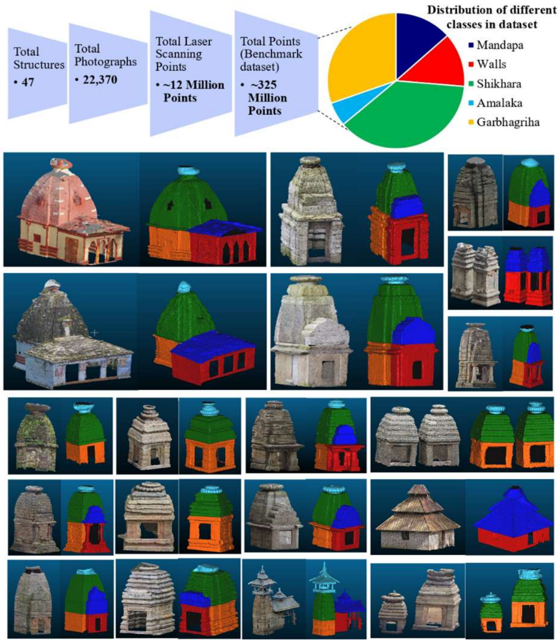


Figure 4. Sample representation of 3DITA dataset

Although the development of benchmark datasets is fundamental for advancing deep learning applications, particularly in 3D semantic segmentation, the point cloud domain lacks universally accepted benchmarking standards. This is primarily due to the domain-specific nature of existing datasets, which often vary significantly in purpose, structure, scale, and data acquisition techniques. As a result, direct comparisons across datasets are inherently limited. Nonetheless, a common approach in scholarly research is to assess newly created datasets against established domain-specific datasets using basic metrics such as the number of scenes, annotated points, and class diversity. Following this strategy, the 3DITA dataset has been compared with several existing point cloud datasets relevant to the cultural heritage and built environment domains. The comparative overview is presented in Table 3, which highlights key attributes of 3DITA alongside prominent datasets identified through an extensive literature review.

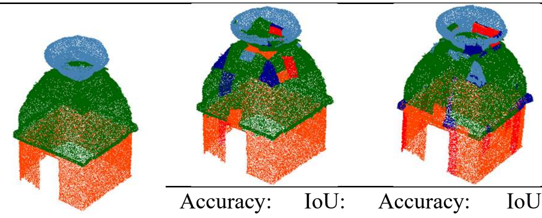
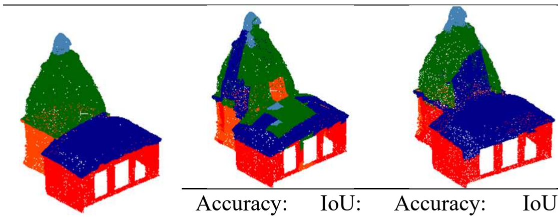
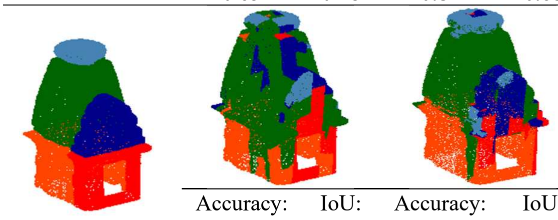
Table 3. Comparison of dataset with other benchmark datasets

S. No	Specific Domain	Heritage Dataset	No. of classes	No. of scenes annotated	No. of Points	References
1.	Chinese Architecture	WHU-TLS Heritage Building	-	11	238.16 million points	(Dong *et al.*, 2020)
2.	Ancient Timber Structure	ATA3D dataset	9	45 (13 real + 32 synthetic)	23 million points	(Guo *et al.*, 2024)
3.	Western & Asian Architecture	ArCH dataset	10	17	130 million points	(Matrone *et al.*, 2020)
4.	Ancient Object	3D Pottery Dataset	-	1012	-	(Lengauer *et al.*, 2021)
5.	Greek Temple Structure	Temple of Hera Dataset	5	1	0.97 million points	(Pepe *et al.*, 2022)
6.	Chinese Ancient Architecture	Self-Built Dataset	9	-	126 million points	(Zhao *et al.*, 2024)
7.	Western Architecture	Synthetic Dataset for Point Cloud Semantic Segmentation	8	2	1.2 billion points (Only few annotated)	(Pan *et al.*, 2024)
8.	Indian Temple Architectures	3DITA Dataset	5	40	325 million points	(ours)

The analysis indicates that 3DITA demonstrates strong comparability in terms of scale and richness. However, it is important to note that dataset size alone cannot serve as a definitive benchmark of quality or utility. Consequently, to further validate the effectiveness of 3DITA, deep learning-based semantic segmentation experiments were conducted.

To assess the effectiveness of the proposed benchmark dataset, two widely adopted deep learning architectures for point cloud semantic segmentation: PointNet and DGCNN were selected for evaluation. PointNet is a pioneering architecture that leverages MLPs to directly process unordered point sets, while DGCNN employs a convolution-based architecture that captures local geometric features using edge convolutions. Three different test structures were evaluated with the trained model and these output results are demonstrated in Table 4.

Table 4. Deep learning based semantic segmentation results

Ground Truth	PointNet		**DGCNN**	
	Accuracy: 0.79	IoU: 0.66	Accuracy: **0.79**	IoU: **0.66**
	Accuracy: 0.65	IoU: 0.48	Accuracy: **0.81**	IoU: **0.68**
	Accuracy: 0.54	IoU: 0.37	Accuracy: **0.76**	IoU: **0.62**

Three test structures from created dataset were selected, each representing varying levels of class complexity and architectural detail. Test Structure 1, comprising only three semantic classes, served as a baseline to assess the model ability to generalize from datasets trained with all five heritage classes. Both PointNet and DGCNN demonstrated strong generalization capabilities, achieving accuracies exceeding 79%, with DGCNN slightly outperforming PointNet. The remaining two test structures contained all five architectural classes: Walls, Mandapa, Shikhara, Amalaka, and Garbhagriha. In Test Structure 2, DGCNN achieved an accuracy of 80%, significantly outperforming PointNet, which reached only 64%. Similarly, in Test Structure 3, DGCNN attained 76% accuracy, whereas PointNet lagged behind at 53%. These results consistently demonstrate the superior performance of DGCNN in handling the geometric complexity and variability inherent in Indian temple architecture. Overall, the evaluation confirms that DGCNN not only surpasses PointNet in segmentation accuracy across multiple structures, but also validates the effectiveness and reliability of the 3DITA benchmark dataset for real-world applications. Its successful performance highlights the potential for deploying deep learning models trained on this dataset in heritage conservation, digital reconstruction, HBIM integration, and preservation efforts for Indian historic structures.

4. Discussions

The development of robust benchmark datasets has become essential for advancing semantic learning using deep neural networks. In the cultural heritage domain, however, researchers (Zhao *et al.*, 2023, 2024; Zhu, Fan and Weng, 2024) have highlighted a significant gap, the scarcity of high-quality, annotated point cloud datasets with sufficient class diversity and architectural representation. This lack of standardized and representative datasets has posed a major challenge for training and evaluating deep learning (DL) models effectively within heritage contexts. Among the few available resources, the ArCH point cloud dataset (Matrone *et al.*, 2020) marked a significant milestone, being the first dataset specifically curated for cultural heritage applications. It catalysed research in DL-based semantic segmentation of heritage structures. However, the ArCH dataset predominantly features Western architectural elements such as churches, cloisters, chapels, and pavilions structures that differ greatly from the architectural vocabulary found in Indian heritage, particularly temple architecture.

To address these limitations, the current study introduced a new dataset tailored to Indian cultural heritage, specifically focused on Nagara-style temple architecture. This architectural style, rooted in ancient Indian traditions and prevalent across northern India, presents distinct geometric and ornamental features that require a contextualized dataset for meaningful DL applications. Recognizing that the success of any DL-based semantic segmentation model depends fundamentally on the quality and representativeness of its training data, this research undertook the careful and resource-intensive creation of a point cloud benchmark dataset. The dataset preparation process involved extensive manual segmentation and quality control to ensure class diversity, spatial richness, and architectural authenticity. The resulting benchmark, named 3DITA (3D Indian Temple Architecture). By filling the gap left by existing datasets, the 3DITA benchmark provides a critical foundation for evaluating semantic segmentation models and supports broader applications in HBIM, digital documentation, and AI-driven heritage analysis.

5. Conclusions

This study underscores the critical role of benchmark datasets in advancing semantic segmentation for cultural heritage applications. It introduces 3DITA—India’s first point cloud benchmark dataset specifically curated for the semantic segmentation of heritage structures. Generated using Close-Range Photogrammetry (CRP) and Terrestrial Laser Scanning (TLS), the dataset comprises over 325 million points from 47 temple structures across 13 sites, manually segmented into five architectural classes characteristic of the Nagara style. The segmentation performance of two leading deep learning models, PointNet and DGCNN, was evaluated on this dataset. Results demonstrate that DGCNN consistently outperformed PointNet, achieving up to 80% segmentation accuracy, highlighting the effectiveness and reliability of the 3DITA dataset for real-world heritage applications.

While the current work focuses on Nagara-style temples and major structural components, its scope can be broadened. Future research should aim to incorporate more granular architectural elements and diverse Indian architectural styles, addressing current limitations in generalizability. Furthermore, integrating and benchmarking additional state-of-the-art models can enhance robustness, though this may introduce higher computational requirements. Ultimately, this study lays the groundwork for scaling up 3D heritage documentation in India, promoting the development of locally optimized, open-source datasets and algorithms tailored for Indian heritage. The availability of 3DITA is expected to catalyse further research in heritage conservation, HBIM, digital twins, and data-driven cultural heritage management.

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