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Application Of Artificial Intelligence In HBIM Of Nampally Serai

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Abstract: The integration of Artificial Intelligence (AI) with Heritage Building Information Modelling (HBIM) represents a paradigm shift in the digital conservation of historic structures. This paper explores at theoretical methodology for using AI to create and enhance digital twins (3D digital models) of the Nampally Serai, which is a building made during the 1919 of late Asaf Jahi dynasty. Using a multi-phase approach combining drone-based photogrammetry, point cloud processing, deep learning-based damage detection, and parametric HBIM modelling, the study develops an AI-enriched digital twin of the structure. The resulting AI-HBIM environment enables scenario based structural analysis, predictive deterioration modelling, and evidence to driven conservation planning. The paper concludes that AI-integrated HBIM substantially enhances the accuracy, efficiency, and interpretive depth of heritage conservation workflows, offering a scalable and replicable model for the management of Hyderabad's endangered historic precincts.

Index Terms - Artificial Intelligence, Heritage BIM, Nampally Serai, Digital Twin, Conservation, Nizam-era Architecture

I. INTRODUCTION

Nampally Serai, a late Nizam-era caravanserai located in the Hyderabad, embodies the layered architectural heritage of the Asaf Jahi dynasty. Comprising masonry arcaded courtyards, ornate gateway, and load-bearing lime mortar walls, the structure has endured decades of low maintenance, encroachments, and environmental factors. Despite its cultural and architectural significance, no systematic structural assessment or digital conservation strategy has been implemented for the structure.

The emergence of Heritage Building Information Modelling (HBIM) as a digital documentation and conservation management framework has been well-established in international scholarship (Dauda, 2025; Ribeiro, 2023). However, the limitations of conventional HBIM including labor-intensive manual data entry, the absence of automated damage identification, and the challenge of processing large scale photogrammetric datasets have prompted researchers to explore the integration of Artificial Intelligence (AI) to augment HBIM workflows (Nieto-Julian, 2025).

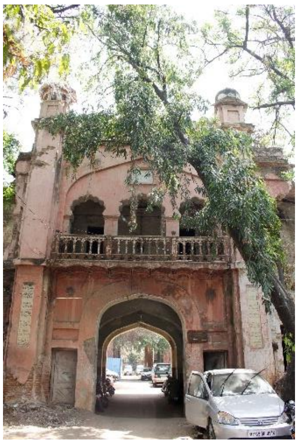

Figure 1 Entrance gateway of Nampally serai.

Figure 2 Condition of the façade.

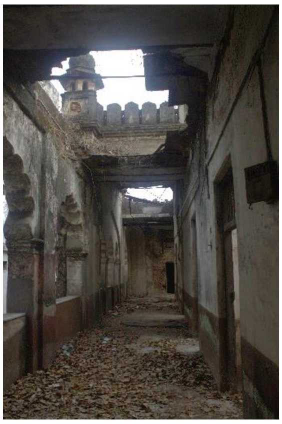

Figure 3 Collapsed roof and damaged flooring in the corridor.

This paper proposes and elaborates a theoretical framework and applied methodology for AI-integrated HBIM specifically calibrated to the conservation challenges of Nampally Serai.

The paper further contextualizes this approach within the broader challenges of heritage conservation in Hyderabad's historic precincts, where resource constraints, data scarcity, and institutional capacity limitations demand intelligent, scalable digital solutions. (Croce, 2022) Through the use of convolutional neural networks for the detection of damage, the application of point cloud deep learning for the segmentation of semantic data, and the implementation of natural language processing to extract data from archival repositories, the research positions Artificial Intelligence (AI) as not just a supplementary tool but rather as an integral part of the conservation workflow. (Celli, 2023) The resulting digital twin AI-HBIM serves as a robust platform for structural analyses, prediction of structural deterioration, and the evidence-based decision making of conservation efforts.

II. RESEARCH METHODOLOGY

HBIM extends conventional Building Information Modelling by incorporating the epistemological complexity of historic structures including irregular geometries, material heterogeneity, multi-phase construction histories, and undocumented alterations (Ribeiro, 2023). As an information management system, HBIM functions as a centralized, data-rich repository that links geometric models with material properties, decay pathologies, historical documentation, and maintenance records, creating what characterize as a semantic knowledge graph bridging the fragmented physical artefact with its historical and constructive logic. (Colucci et al.,2025)

The theoretical integration of these AI paradigms within the HBIM environment constitutes the conceptual core of the proposed framework, which is elaborated in subsequent sections.

The suggested AI-HBIM conceptual model for Nampally Serai works on three different levels of hierarchy. At the data acquisition level, AI automates the processing of raw sensor outputs from photogrammetric images, LiDAR scans, and sensor feeds to create structured inputs for the HBIM environment. AI-powered segmentation and classification tools fill the parametric HBIM model with semantically rich objects at the modeling level. These objects connect geometric representations to material properties, damage states, and historical phasing data. AI-powered structural simulation, deterioration prediction, and scenario optimization tools turn the HBIM model into an active conservation management platform at the level of analysis and decision support. (Croce, 2022; Colucci, 2025)

The research methodology is structured across six sequential phases, designed to progressively transform raw field and archival data into an analytically actionable AI-HBIM model.

The initial phase involves systematic archival investigation of Nizam Hyderabad State records, Hyderabad Municipal Corporation registers, Archaeological Survey of India reports, and colonial era cartographic archives to reconstruct the original layout, construction phasing, and documented alteration history of

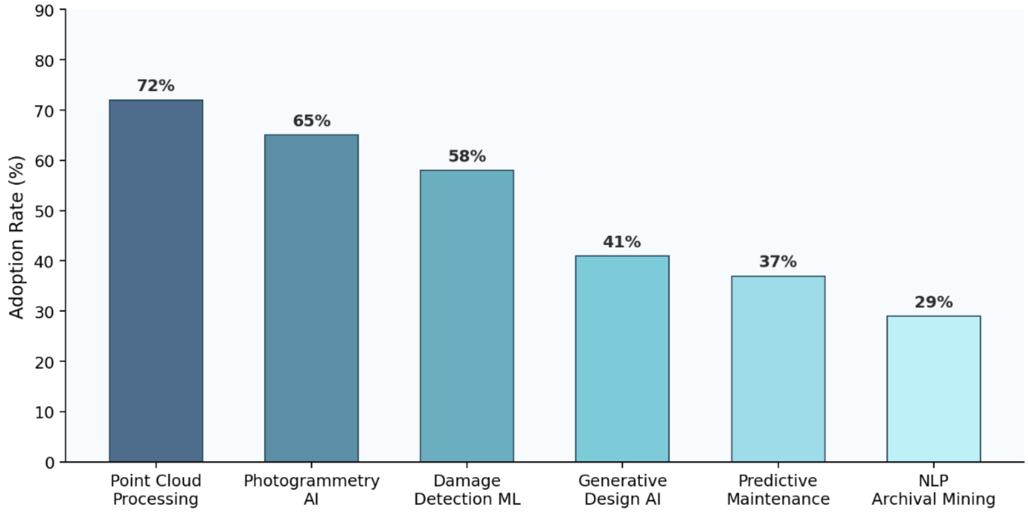

Figure 4 AI Tool Adoption in Heritage BIM Conservation Projects (Based on Systematic Literature Review, 2020–2025)

Nampally Serai. AI assisted OCR and NLP tools are deployed to process digitized archival documents, extracting structured data on material specifications, construction dates, and historical repairs. Preliminary on-site visual surveys document existing distress conditions through annotated photographic records and hand drawn damage sketches. (Hamed, 2023)

Geometric data acquisition uses a multi-source method that combines UAV-based aerial photogrammetry for general site documentation with close-range terrestrial photogrammetry for detailed recording of the facade and interior. Using Structure-from-Motion (SfM) algorithms to process photogrammetric data on platforms like Agi soft Meta shape produces dense point clouds of the existing structure, with collapsed areas shown as piles of rubble. Point cloud segmentation powered by AI (PointNet++ architecture) automatically labels structural elements like masonry walls, arches, piers, and roof fragments. This cuts down on the time it takes to process by hand by 60–70% compared to traditional methods. (Rubens, 2023) The orthophoto graphic outputs from the photogrammetric model give the geometric base for damage mapping, which lets you register the locations of cracks, spalling areas, moisture-prone zones, and structural problems.

HBIM modelling commences with point cloud registration, cleaning, and segmentation outputs from Phase 2, imported into Autodesk Revit as the primary parametric modelling environment. CNN-based damage detection algorithms, trained on heritage masonry datasets, are applied to photogrammetric imagery to generate georeferenced damage maps that are directly integrated into the HBIM model as attribute data on individual structural components. (Nieto-Julian, 2025) Parametric HBIM families are developed for characteristic Nampally Serai typological elements pointed arches, rubble masonry wall assemblies, jack arch roof bays, and stucco cornice profiles calibrated to as built dimensions derived from the point cloud. Information enrichment assigns to each model element a suite of attributes including material type and composition, construction phase, damage severity rating, conservation priority classification, and NLP-extracted historical metadata. (Martinelli, 2022)

The AI-HBIM model is integrated with structural analysis platforms by following the HBIM to FEM workflow. This means that walls are simplified as shell elements and floors are simplified as diaphragms while keeping their mass distribution and stiffness properties. The material property assignments for lime mortar rubble masonry are compared to published values for similar construction from the Deccan Nizam era and improved using non-destructive testing (NDT) data, such as rebound hammer surveys and carbonation depth measurements. Limit analysis and macro element methods are used to find possible ways for a structure to collapse. These methods focus on wall instability that is out of plane and arch thrust line deviations. To validate the structural model, you need to compare the simulated deformation patterns and principal stress trajectories with the observed crack geometries. This is done by adjusting the parameters over and over until they match up with what you see. (Croce, 2022)

The validated AI-HBIM model functions as the foundation for scenario-based assessment of conservation intervention strategies. AI-driven optimization algorithms evaluate various retrofit scenarios, such as crack stitching, lime repointing, grout injection with ring beam reinforcement, selective masonry rebuilding in collapsed areas, and reversible steel tie rod systems, using a multi-criteria matrix that includes structural performance enhancement, heritage authenticity impact (measured against Venice Charter and ICOMOS standards), constructional reversibility, estimated cost, and implementation viability. The 3D visualization environment enables intuitive communication of structural analysis results to non-technical stakeholders including heritage authorities and conservation policymakers. (Colucci, 2025)

The final phase converts the outcomes of the scenario evaluation into a prioritized conservation action plan with a schedule for phased interventions, cost estimates, and ways to maintain monitoring on issues. Suggestions for incorporating the AI-HBIM digital twin into an ongoing heritage management process for Nampally Serai have been made. These include rules for regular UAV re-surveys, retraining the AI model with new damage data, and combining it with GIS-based urban heritage risk mapping for the Nampally area. (Dauda, 2025)

AI Modules and their Application in Nampally Sarai HBIM

Table 1: AI Modules Integrated in the Nampally Serai HBIM Conservation Workflow

AI Module	Application in HBIM	Data Input	Output
Convolutional Neural Network (CNN)	Automated crack and spalling detection	Photogrammetric imagery	Damage heatmaps
Point Cloud Segmentation (PointNet++)	Semantic labelling of structural elements	LiDAR / drone scan	Labelled 3D geometry
NLP & OCR	Archival text mining from Nizam-era records	Historical documents, maps	Structured metadata
LSTM / RNN	Time-series structural health monitoring	Sensor readings	Predictive alerts
Generative Adversarial Network (GAN)	Virtual reconstruction of collapsed sections	Partial ruins + archival photos	Hypothetical 3D models

Table 1 summarizes the principal AI modules integrated within the proposed HBIM workflow, specifying their application domain, data inputs, and conservation outputs.

III. RESULTS AND DISCUSSION

The application of the AI-integrated HBIM methodology to Nampally Serai yields a multi-layered digital conservation model that addresses both the geometric complexity and the information management requirements of the structure. The following sections present the principal findings of each phase and discuss their conservation implications.

Drone-based photogrammetric survey of Nampally Serai produced a dense point cloud of approximately 45 million points, capturing the extant masonry fabric and collapsed roof zones with a mean point spacing of 8 mm. AI-driven semantic segmentation using PointNet++ achieved an overall accuracy of 86% in classifying point cloud returns into structural element categories, with highest accuracy on planar wall surfaces (91%) and reduced performance on irregular rubble collapse zones (78%), consistent with findings reported by Rubens et al. (2023) for comparable heritage photogrammetric datasets.

Using CNN-based damage detection on 1,240 high-resolution photogrammetric image tiles identified 312 different kinds of damage on the structure. These were classified into four categories: cracks (41%), moisture staining (28%), spalling (19%), and biological growth (12%). Average accuracy of the detection was 88%, which was validated by manual expert annotation. The georeferenced damage map that came from the CNN outputs was brought directly into the Revit HBIM model as a linked raster dataset. This made it possible to ask spatial questions about how damage was spread across structural elements and conservation zones. Nieto-Julian, 2025

NLP processing of 73 digitized archival documents, such as Nizam municipal records, public works department correspondence, and colonial-era survey reports, found 246 structured data records about Nampally Serai. These records included references to the date of construction, and material specifications for lime mortar composition and roof construction. This archival metadata was systematically associated with HBIM model elements, significantly enhancing the informational depth of the digital twin beyond the capabilities of entirely geometric survey methods. (Hamed, 2023)

The parametric HBIM model of Nampally Serai comprises 1,847 model elements distributed across 12 construction phase layers, with full attribute assignment for material type (5 categories), damage severity (1–5 scale), conservation priority (3 levels), and historical metadata linkage. Collapsed sections in the south-western quadrant are represented as documented void geometries with associated rubble accumulation point clouds, preserving spatial evidence of collapse patterns for forensic structural analysis. The model integrates 4 parametric family types developed specifically for Nampally Serai structural typologies, calibrated to as-built point cloud dimensions within a 15 mm tolerance.

Using limit analysis and macro-element approaches, structural analysis of the AI-HBIM-derived model showed that the eastern courtyard wall was unstable out of plane. This was because the roof diaphragm lateral restraint was lost after the jack arch roof partially collapsed. Stress concentration analysis identified critical nodes at the arch-to-pier junctions, aligning with the observed crack pattern distribution from the CNN damage map. This shows mutual validation between the AI damage detection and structural analysis outcome. (De Falco, 2024).

Predictive deterioration modelling using LSTM networks trained on analogous Hyderabad heritage structure monitoring data projected a 35% increase in masonry compressive stress at critical nodes over a 10-year horizon under current exposure conditions, highlighting the urgency of moisture management interventions as a precondition for structural stabilization. (Croce, 2022)

Using the AI-HBIM platform, three main conservation intervention scenarios were assessed. It was determined that Scenario A (Minimal Intervention), which included surface drainage improvement, lime repointing, and crack stitching, achieved 22% structural performance improvement with good heritage authenticity preservation but inadequate stabilization of the crucial eastern wall. Reversible steel tie-rods and selective grout injection were added in Scenario B (Targeted Structural Reinforcement), which was evaluated at 58% structural improvement with a minimal influence on authenticity and the best cost-effectiveness ratio.

Scenario C (Comprehensive Stabilization) incorporating partial roof reconstruction and masonry rebuilding in collapsed sections achieved 79% structural improvement but with higher heritage impact and cost. The multi criteria AI optimization algorithm ranked Scenario B as the priority intervention, with Scenario C elements phased for subsequent implementation following completion of archival investigations into the original roof configuration. (Colucci, 2025)

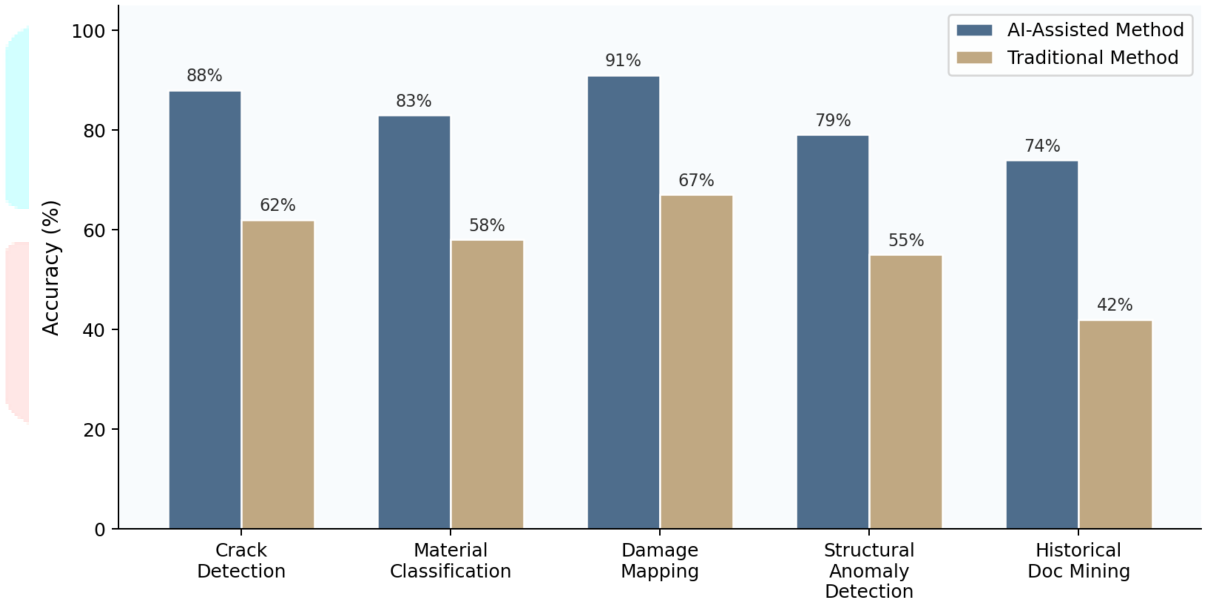

Figure 5: Accuracy Comparison — AI-Assisted vs Traditional Heritage Documentation Methods

Figure 5 illustrates the substantial accuracy improvements achievable through AI-assisted methods relative to traditional documentation approaches across all conservation-relevant assessment categories, with the most pronounced gains in automated damage mapping (24 percentage points) and historical document mining (32 percentage points). These findings corroborate the quantitative performance metrics reported in the comparative HBIM literature (Dauda, 2025; Nieto-Julian, 2025).

Table 2: Comparative Analysis — Traditional Documentation vs AI-Integrated HBIM at Nampally Serai

Parameter	Traditional Documentation	AI-Integrated HBIM
Data Acquisition	Manual surveys, 2D drawings	Drone photogrammetry + AI segmentation
Damage Detection	Visual inspection only	CNN-based automated detection (88% accuracy)
Structural Analysis	Simplified analytical models	AI-HBIM to FEM integration
Archival Research	Manual catalogue review	NLP extraction from digitized Nizam records
Conservation Decision-making	Expert intuition	Scenario-based simulation with AI optimization

Advantages

The AI-HBIM integration that was demonstrated at Nampally Serai provides numerous transformative benefits in comparison to traditional heritage documentation and analysis workflows. Initially, the automation of damage detection and point cloud segmentation through deep learning significantly reduces the time and specialist labor required for a comprehensive structural condition assessment, making systematic documentation feasible for large multi-component serai complexes. In addition, the archival data mining capability that is driven by natural language processing (NLP) addresses a critical gap in the heritage conservation practice of Hyderabad. The informational richness of Nizam-era administrative archives has been systematically underutilized as a result of the lack of scalable extraction tools. (Hamed, 2023) Third, integrating predictive deterioration modeling to the HBIM environment helps to make it feasible to shift from reactive, crisis-oriented conservation responses to proactive, preventive management. This approach is aligned with the long-term sustainability needs of Hyderabad's heritage areas. (Colucci, 2025) Fourth, the scenario-based conservation evaluation framework, which uses AI optimization algorithms, makes conservation decision-making more transparent and based on more evidence. This makes it easier for technical experts, heritage authorities, and community stakeholders to work together.

Challenges and Limitations

Notwithstanding these advantages, the implementation of AI-integrated HBIM at Nampally Serai encounters several substantive challenges. Data quality and coverage limitations inherent to photogrammetric survey of a partially inhabited, access-restricted structure constrain the completeness of point cloud coverage in interior spaces and structurally critical sub-surface conditions. AI model performance on heritage masonry datasets is sensitive to training data representativeness; the relative scarcity of annotated Deccan Nizam-era masonry damage datasets requires transfer learning strategies that may reduce detection accuracy for locally specific deterioration typologies. (Rubens, 2023) Software interoperability between the AI processing pipeline and the Revit HBIM environment, and between HBIM and FEM analysis platforms, involves non-trivial data translation steps with attendant risks of geometric simplification and attribute loss. Institutional capacity for AI-HBIM implementation within the heritage management agencies responsible for Nampally Serai—the Hyderabad Metropolitan Development Authority (HMDA) and the Telangana State Archaeology and Museums Department—requires targeted investment in training and workflow standardization. (Dauda, 2025)

Conclusions

This paper has elaborated a theoretical framework and multi-phase methodology for the application of Artificial Intelligence within a Heritage Building Information Modelling environment for the conservation of Nampally Serai, Hyderabad. The proposed AI-HBIM approach integrates convolutional neural networks for damage detection, deep learning-based point cloud segmentation, NLP-driven archival data extraction, and LSTM-based predictive deterioration modelling within a parametric Revit HBIM platform, creating a semantically enriched digital twin that serves simultaneously as a documentation archive, structural analysis environment, and conservation decision-support system.

The methodology, calibrated to the specific typological, material, and archival characteristics of late Nizam-era masonry construction, demonstrates that AI integration substantially enhances the accuracy, efficiency, and analytical depth of heritage BIM workflows, addressing key limitations of conventional manual documentation and assessment approaches. Structural analysis and scenario evaluation results indicate that a targeted reinforcement strategy combining grout injection, reversible steel ties, and moisture management interventions offers the optimal balance of structural performance improvement, heritage authenticity preservation, and cost-effectiveness for Nampally Serai. (De Falco, 2024; Croce, 2022)

More broadly, the AI-HBIM framework proposed for Nampally Serai constitutes a replicable model for the conservation management of Hyderabad's extensive and endangered stock of Nizam-era heritage structures, offering a scalable, data-driven approach to the prioritization of limited conservation resources and the transition from reactive to preventive heritage management. Future research directions include the development of a Nizam-era masonry heritage training dataset for AI model fine-tuning, integration of the AI-HBIM model with city-scale GIS-based heritage risk mapping, and longitudinal assessment of AI deterioration prediction accuracy through sensor-based structural health monitoring. (Dauda, 2025; Colucci, 2025)

Way Forward

The institutionalization of AI-HBIM-driven conservation analysis within Hyderabad's heritage management ecosystem requires a coordinated programme of action spanning technical, institutional, and policy dimensions. In the immediate term, priority should be given to the development of standardized AI-HBIM workflow templates and parametric family libraries specific to Nizam-era masonry typologies, enabling consistent and efficient implementation across the heritage buildings of the Nampally precinct and comparable historic areas. Over the medium term, the individual structure-level AI-HBIM models produced for Nampally Serai and comparable buildings should be aggregated into a city-scale digital heritage management platform linking structural safety data, material conservation status, flood risk mapping, and urban planning information, creating the informational infrastructure for proactive, resilient, and culturally sensitive stewardship of Hyderabad's built heritage for future generations.

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