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LEVERAGING LARGE ARTIFICIAL INTELLIGENCE MODELS FOR THE REVITALIZATION OF SUAKIN ISLAND, SUDAN

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Abstract
Suakin Island, located on the Red Sea coast of eastern Sudan, represents one of the most significant yet endangered examples of coral-stone Islamic architecture in the world. Once a thriving Ottoman-era port city, Suakin's distinctive urban fabric — characterized by mashrabiyas (wooden lattice screens), multi-story coral-stone mansions, arcaded markets, and intricately carved wooden doors — has suffered severe deterioration over the past century. This paper proposes and details a comprehensive framework for applying Large Artificial Intelligence (AI) Models to the digital revitalization, documentation, classification, and predictive restoration of Suakin's architectural heritage and that of broader eastern Sudan. Drawing on the latest advances in Large Language Models (LLMs), Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), Generative Adversarial Networks (GANs), and diffusion-based generative models, we outline a full pipeline: from field data collection and feature engineering of architectural elements, to training supervised classifiers and generative restoration models. We benchmark applicable methods from analogous heritage contexts (Chinese, Iranian, Greek, and Indonesian vernacular architecture) where accuracies exceeding 90–98% have been achieved. We identify critical research gaps — the absence of any dedicated dataset or end-to-end AI model for Suakin — and propose concrete methodological pathways to address them. The study further introduces ArchGPT-style reasoning agents and multimodal CLIP-based retrieval as novel tools for supporting architectural conservation professionals in Sudan. Our findings establish that, given targeted data collection and culturally grounded model training, AI-based systems can serve as transformative instruments for the preservation and revitalization of Suakin Island's irreplaceable built heritage.
Keywords: Suakin Island; Sudan architectural heritage; Large Language Models; Convolutional Neural Networks; feature engineering; generative AI; heritage revitalization; Islamic architecture; coral-stone buildings; transfer learning

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I. INTRODUCTION

Suakin (also spelled Sawakin or Souakin) is a small island city located approximately 58 km south of Port Sudan on the Red Sea coast of eastern Sudan. Historically one of the most important commercial and pilgrimage ports in the Islamic world, Suakin flourished between the 16th and early 20th centuries as a major node on the Red Sea trade routes, connecting the Nile Valley with Arabia, Persia, India, and beyond. At its height, the city featured a dense urban fabric of two- to three-storey coral-stone buildings, elaborate Ottoman-influenced mansions owned by wealthy merchants, mosques, caravanserais, and a distinctive waterfront that drew travelers and traders from across the known world.

The decline of Suakin began with the construction of the modern port city of Port Sudan in 1909, which diverted maritime traffic and commerce. Since then, the city has been largely abandoned, and its distinctive coral-stone buildings — many of which were constructed without mortar using the naturally porous coral blocks quarried from the nearby reefs — have progressively crumbled. Today, Suakin is recognized internationally as one of the most endangered heritage sites in the world, with ongoing conflicts in Sudan having further accelerated its deterioration.

Despite its historical and architectural significance, Suakin has received comparatively little attention in the global heritage AI research community. Existing documentation relies primarily on Jean-Pierre Greenlaw's seminal 1976 monograph on the coral buildings of Suakin, a small number of architectural surveys, and most importantly the parametric shape-grammar study by AbdulRaheem Bolaji and Rayis (2016) \u2014 the only published computational model built directly from Suakin's traditional house typology. No dedicated large-scale AI model, annotated dataset, or deep learning classification pipeline has been developed specifically for Suakin or the broader eastern Sudan architectural tradition. This represents a critical gap in both heritage science and applied AI research.

This paper addresses this gap by proposing a comprehensive, methodologically grounded framework for applying Large AI Models to the revitalization of Suakin Island. Our objectives are four-fold:

1. To survey the state of the art in AI-driven heritage image classification and generative modeling, identifying methods directly transferable to the Suakin context.
2. To propose a complete feature engineering pipeline for Suakin's architectural elements, including data collection, annotation, preprocessing, and model training protocols.
3. To design and evaluate classification and predictive restoration models adapted from analogous heritage contexts, with documented performance benchmarks.
4. To discuss the ethical, cultural, and community-engagement dimensions necessary for responsible AI deployment in Sudan's heritage landscape.

The remainder of this paper is organized as follows: Section 2 provides background on Suakin's architectural heritage. Section 3 reviews related work in AI-based heritage analysis. Section 4 presents our proposed methodology and model architecture. Section 5 discusses dataset construction and feature engineering. Section 6 details the classifier and generative model training pipeline. Section 7 addresses ethical considerations. Section 8 presents preliminary results from analogous cases. Section 9 identifies open research questions, and Section 10 concludes.

II. SUAKIN ISLAND: ARCHITECTURAL HERITAGE AND CULTURAL SIGNIFICANCE

2.1 Historical and Urban Context

Suakin's built environment reflects over five centuries of layered architectural influence. The city's urban morphology is characterized by a compact island core (the Jazira) connected by a causeway to the mainland settlement (Al-Qeyf). The Jazira features densely packed residential mansions, mosques, a customs house, and commercial buildings, all organized around narrow shaded alleys and semi-public courtyards. This spatial organization is both climatically adaptive — minimizing solar exposure and channeling coastal breezes — and culturally expressive of Islamic urban planning principles.

The architectural vocabulary of Suakin draws from Ottoman Turkish, Yemeni, Hijazi, Indian, and indigenous Sudanese traditions. Key typological features include:

- Coral-stone construction: porous, load-bearing blocks quarried from the Red Sea reef, providing thermal mass and natural ventilation.
- Mashrabiya (wooden lattice screens): projecting oriel windows that screen private family spaces from public view while allowing airflow.
- Roof terraces (Kharjah): elevated sleeping and gathering platforms designed to capture nighttime cooling breezes.
- Intricately carved wooden doors and lintels: reflecting Indian (particularly Gujarati) craftsmanship.
- Central courtyards: organizing circulation and dividing public (men's majlis) from private (women's harem) zones.

2.2 Current State of Deterioration

Most of Suakin's coral-stone buildings have collapsed or are in advanced states of ruin. The coral-stone material, while climatically ideal, is structurally fragile when deprived of regular maintenance. Decades of saltwater erosion, vegetation penetration, neglect, and more recently the direct and indirect effects of Sudan's ongoing civil conflict have compounded structural failures. UNESCO and the Aga Khan Trust for Culture have intermittently supported documentation efforts, but a systematic, AI-assisted condition assessment and predictive restoration framework has not been undertaken.

2.3 Previous Documentation Efforts

Existing documentation includes Greenlaw's photographic and measured drawings from the 1970s, architectural surveys by the French Archaeological Section in Sudan, and more recently the foundational parametric shape-grammar model developed by AbdulRaheem Bolaji and Rayis (2016). Published in the International Journal of Computer-Aided Technologies, that study constitutes the most rigorous computational analysis of Suakin's traditional architecture to date. The model encodes the formal vocabulary of Suakin house plans as parameterized 2D shapes with explicit adjacency rules: entrance on the short side, courtyard positioned in front of the women's majlis, and standardized dimensional ranges for the primary space, harem entrance, rooms, and openings. The design process proceeds stepwise \u2014 defining the grid, primary and secondary spaces, entrances, circulation paths, openings, and decorative details \u2014 yielding a wide family of valid plan layouts consistent with Suakin's modular, symmetrical architectural character. While this shape-grammar work provides a uniquely structured, site-specific representation of Suakin's architectural logic and constitutes an invaluable foundation for the AI models proposed in this paper, it remains a rule-based generative engine rather than a data-driven statistical predictor. The transition from Bolaji and Rayis's grammar-based generation to the machine-learning classification and prediction models proposed here is the central methodological contribution of our work.

III. RELATED WORK: AI IN ARCHITECTURAL HERITAGE ANALYSIS

3.1 Deep Learning for Heritage Building Classification

The application of deep learning to architectural heritage analysis has advanced rapidly since 2018. Convolutional Neural Networks (CNNs) — including ResNet, VGG16, EfficientNet, DenseNet, and MobileNet architectures — have been widely applied to classify architectural styles, building types, and individual elements from photographic and remote-sensing imagery. Benchmark studies report test accuracies ranging from 86% to 98% on well-labeled datasets. For instance, HistoNet, a CNN-based model trained on the Architectural Heritage Elements dataset (10 element classes including altars, apses, bell towers, columns, and domes), achieved 96.46% accuracy. A Swin Transformer-based model for traditional Chinese historical buildings exceeded 97.8% across accuracy, precision, recall, and F1 metrics.

More recently, Vision Transformers (ViTs) and hybrid CNN-Transformer architectures (such as HeritageNet) have demonstrated improved performance by capturing both local texture features and global spatial dependencies within heritage imagery. These models are particularly relevant for Suakin, where the interplay of surface texture (coral-stone grain, lime plaster finish, wood decay patterns) and spatial composition (fenestration rhythm, arcade proportions) constitutes the primary visual signature.

3.2 Generative Models for Heritage Reconstruction

Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and diffusion models have been successfully employed for the virtual reconstruction and design exploration of heritage buildings. These approaches generate plausible visualizations of deteriorated or missing elements by learning the latent distribution of architectural features from training corpora. When trained on localized datasets — for instance, datasets specific to Emirati vernacular architecture or Korean urban neighborhoods — these models produce culturally accurate outputs that outperform generic pre-trained alternatives.

ArchGPT, published in npj Heritage Science (2024), represents a notable advance: an AI agent built on Large Language Model (LLM) reasoning capabilities that coordinates task-specific sub-models (facade parsing, element recognition, style transfer) to support end-to-end architectural renovation workflows. Such LLM-orchestrated pipelines are directly applicable to Suakin, where conservation professionals require multi-step decision support integrating spatial analysis, material assessment, and style-consistent design generation.

3.3 Remote Sensing and UAV Applications

Satellite imagery and UAV photogrammetry have been used to detect and classify vernacular buildings in regions with limited ground access. Mask R-CNN applied to satellite imagery in Khartoum demonstrated the feasibility of building extraction in Sudanese urban contexts, achieving average precision (AP@0.50:0.95) of approximately 71.9. These methods are particularly relevant for Suakin, where security constraints and physical deterioration may limit traditional survey access.

3.4 Feature Engineering for Architectural Classifiers

Effective AI classification of architectural elements requires careful feature engineering that captures both visual and semantic dimensions. Common approaches include: extraction of HOG (Histogram of Oriented Gradients) and SIFT descriptors for ornamental pattern recognition; deep feature extraction using pre-trained CNN backbones followed by classical ML classifiers (SVM, Random Forest, XGBoost); attention-based feature weighting to highlight discriminative elements; and CLIP-based multimodal embeddings that align visual features with textual descriptions (e.g., 'coral-stone facade,' 'mashrabiya screen,' 'Ottoman carved lintel'). The XGBoost-SHAP explainability framework has proven particularly effective for identifying the specific spatial features that distinguish regional architectural styles, offering interpretable outputs valuable to heritage professionals.

3.5 Regional Gaps and Transfer Learning Potential

A systematic review of the literature identifies only one published computational study targeting Suakin's own architectural elements: the parametric shape-grammar model by AbdulRaheem Bolaji and Rayis (2016), which provides a formal generative encoding of traditional Suakin house plans based on empirical documentation of the site. While this work is indispensable as a structured architectural knowledge base, it predates the deep learning era and does not constitute a data-driven predictive or classification model. No subsequent AI study has built upon it or developed an end-to-end classifier for Suakin's visual elements or the broader eastern Sudan built heritage. This gap reflects both the general underrepresentation of sub-Saharan African and Red Sea regional architectures in the global AI heritage research agenda and the practical challenges of data collection in conflict-affected environments. However, Bolaji and Rayis's structured spatial vocabulary \u2014 its parameterized room dimensions, adjacency rules, and formal element definitions \u2014 provides precisely the feature ontology needed to bootstrap an AI training dataset, and the demonstrated success of transfer learning from Asian and Middle Eastern heritage datasets provides a clear methodological pathway for bridging this gap.

IV. PROPOSED METHODOLOGY AND MODEL ARCHITECTURE

4.1 Overall Framework

We propose a four-stage pipeline for AI-driven Suakin architectural revitalization, as illustrated conceptually in the framework below. The pipeline integrates data acquisition, feature engineering, model training, and deployment phases, each designed to address the specific challenges and opportunities of Suakin's architectural context.

Stage	Phase 1	Phase 2	Phase 3	Phase 4
Name	Data Collection	Feature Engineering	Model Training	Deployment
Key Tools	UAV / Photogrammetry / Archives	CNN Backbones / HOG / CLIP	ResNet / ViT / GAN / LLM	ArchGPT / Web API
Output	Annotated Image Dataset	Feature Vectors / Labels	Trained Models	Interactive Conservation Tool

Table 1: Four-Stage AI Pipeline for Suakin Architectural Revitalization

4.2 Data Acquisition Strategy

Given the absence of an existing labeled dataset for Suakin, data acquisition is the foundational and most critical step. We propose a multi-source data collection protocol combining:

- UAV/drone photogrammetry: High-resolution aerial and oblique imagery of surviving structures on Suakin Island and mainland Al-Qeyf, generating photorealistic 3D point clouds and orthophotos.
- Historical archive digitization: Scanning and georeferencing Greenlaw's measured drawings, French Archaeological Section records, Aga Khan documentation, and colonial-era photographs.
- Ground-level photographic survey: Systematic facade and element documentation using calibrated DSLR/mirrorless cameras following standardized protocols.
- Satellite remote sensing: Multispectral imagery for urban morphology mapping and structural condition assessment.

4.3 Annotation Protocol

Collected imagery will be annotated using a hierarchical labeling scheme developed collaboratively with Sudanese architectural historians and conservation professionals. The annotation taxonomy distinguishes three levels:

- Building-level: Type (residential mansion, mosque, caravanserai, market hall), period (Ottoman, Khedival, British colonial), and conservation status (intact, partially ruined, collapsed).
- Facade-level: Composition features including number of stories, window rhythm, portal design, cornice treatment, and surface finish.
- Element-level: Individual architectural elements including mashrabiya screens, carved wooden doors, coral-stone block patterns, decorative stucco, and structural arches, each with geometric attributes (dimensions, proportions, orientation).

4.4 Model Architecture Selection

Based on our review of the heritage AI literature, we propose a staged model architecture selection strategy:

Task	Recommended Model	Expected Accuracy	Reference Context
Element Classification	ResNet-50 / EfficientNet-B3	90–96%	Arch. Heritage Elements Dataset
Style Recognition	Swin Transformer / ViT	95–98%	Chinese / Iranian datasets
Damage Detection	YOLOv8 / Swin+YOLOv5	>99% class accuracy	Gulang Island (UNESCO)
Element Reconstruction	GAN / Diffusion Model	Qualitative (FID <30)	Emirati vernacular GAN
Design Assistance	ArchGPT (LLM Agent)	Task-completion rate	npj Heritage Science 2024
Multimodal Retrieval	CLIP + SVM	mAP 76–98%	Chinese diaspora architecture

Table 2: Recommended AI Models for Each Suakin Analysis Task and Expected Performance Benchmarks

V. FEATURE ENGINEERING FOR SUAKIN ARCHITECTURAL ELEMENTS

5.1 Visual Feature Extraction

Visual feature extraction forms the core of our classification pipeline. For each annotated image or image crop, we extract features at multiple levels of abstraction:

5.1.1 Low-Level Texture Features

Coral-stone's characteristic surface texture — defined by its irregular porosity, warm beige-to-cream coloration, and biotic surface patterns from marine organism remnants — provides a discriminative signature for material classification. We extract Local Binary Pattern (LBP) histograms, Gabor filter bank responses, and Gray-Level Co-occurrence Matrix (GLCM) features to characterize coral-stone versus lime-plaster versus wood surfaces. These features, shown to be highly effective in material classification tasks, will be concatenated into a multi-scale texture descriptor.

5.1.2 Mid-Level Shape and Geometry Features

Geometric features capture the proportional relationships and formal patterns characteristic of Suakin architecture. Derived features include: aspect ratio and fenestration density (windows-per-facade-area), mashrabiya grid geometry (module size, lattice pattern type), arch profile classification (pointed, segmental, horseshoe), and door carving complexity indices derived from edge density maps. These features will be extracted using a combination of classical computer vision (Canny edge detection, Hough transforms for line detection) and CNN-derived intermediate feature maps.

5.1.3 High-Level Semantic Features

Deep semantic features are extracted from the penultimate layers of pre-trained CNN backbones (ResNet-50, EfficientNet-B3) fine-tuned on our Suakin dataset. These 2048-dimensional feature vectors capture compositional and stylistic properties that transcend simple texture or geometry, encoding learned representations of 'Suakin-ness' directly from data. We additionally employ CLIP (Contrastive Language-Image Pre-training) to generate joint visual-textual embeddings by pairing images with expert-authored descriptive captions such as 'Ottoman-era coral-stone mansion with projecting mashrabiya on second floor.'

5.2 Geometric and Topological Features

Beyond visual features, we encode the topological relationships between architectural elements — drawing directly on the parameterized spatial vocabulary established by AbdulRaheem Bolaji and Rayis (2016) for Suakin — as graph-structured features. Each building plan is represented as a spatial adjacency graph where nodes correspond to rooms, courtyards, entrances, and service spaces, and edges encode adjacency, hierarchical containment, or visual axis relationships. The dimensional parameters formalized in that shape-grammar study (standardized ranges for courtyard width, primary space proportions, harem entrance dimensions, and opening positions) directly populate the node attribute vectors of our graph representation. Graph Neural Networks (GNNs) are proposed as a complementary model for plan-type classification that explicitly captures the relational structure of Suakin's spatial organization.

5.3 Temporal and Condition Features

For predictive condition assessment and restoration priority modeling, we derive temporal and degradation features from multi-epoch satellite imagery (comparing imagery from different years) and from surface defect annotations. Degradation indicators include crack density, vegetation encroachment index (derived from spectral NDVI analysis), wall height loss (compared against historical measured drawings), and structural leaning angle (from 3D point cloud analysis). These features will be used to train regression models predicting further deterioration rates and identifying buildings requiring urgent intervention.

VI. CLASSIFIER AND GENERATIVE MODEL TRAINING PIPELINE

6.1 Data Preprocessing and Augmentation

Given the anticipated scarcity of labeled training samples — a fundamental challenge for any domain-specific heritage AI project — we implement an extensive data augmentation strategy inspired by analogous small-dataset heritage classifiers. Augmentations include geometric transforms (rotation ±15°, horizontal flip, random crop), color jittering (brightness, contrast, saturation perturbation within climatically plausible ranges), noise injection (Gaussian noise, salt-and-pepper), and histogram equalization to simulate varying lighting conditions across Suakin's coastal environment. Synthetic data generation using style-transfer GANs trained on combined Middle Eastern and eastern African architectural datasets will supplement real imagery where labeled samples are insufficient.

6.2 Transfer Learning Protocol

All deep learning classifiers will be initialized from ImageNet pre-trained weights and subsequently fine-tuned on our Suakin dataset using a differential learning rate schedule (lower learning rates for early convolutional layers, higher for task-specific classification heads). Transfer learning from architecturally adjacent domains — specifically Yemeni Hijazi-style architecture, Egyptian Islamic heritage, and Indian Gujarati woodwork — provides culturally relevant source domains that share visual and formal features with Suakin, minimizing the domain shift that would result from transfer directly from East Asian or European datasets.

6.3 Supervised Classification Training

Binary and multi-class classifiers for element recognition (e.g., mashrabiya presence/absence, door style classification, arch typology) will be trained using cross-entropy loss with class-weighted sampling to address dataset imbalance. Model evaluation will employ stratified k-fold cross-validation (k=5) with a held-out test set comprising images from buildings not represented in training. Primary metrics include accuracy, macro-averaged F1, precision, recall, and Area Under the ROC Curve (AUC-ROC). Explainability will be provided via Grad-CAM saliency maps and SHAP value analysis, enabling architectural scholars to verify that model decisions are grounded in genuinely discriminative visual features.

6.4 Generative Restoration Modeling

For the generative reconstruction of missing or deteriorated architectural elements, we propose training a conditional GAN architecture (specifically a Pix2Pix or StyleGAN3 variant) on paired data: degraded element images paired with restoration targets drawn from historical photographs and expert-reconstructed drawings. The generator learns to hallucinate plausible restored states conditioned on structural context (remaining wall geometry, adjacent intact elements, plan configuration), while the discriminator enforces style consistency with authentic Suakin architectural vocabulary. Fréchet Inception Distance (FID) and Structural Similarity Index (SSIM) will serve as quantitative restoration quality metrics, supplemented by expert panel evaluation.

6.5 LLM-Orchestrated Conservation Agent

Building on the ArchGPT paradigm, we propose training a domain-adapted LLM agent for Suakin conservation support. A base LLM (such as an open-source LLaMA variant or GPT-4o via API) will be fine-tuned and prompt-engineered with a Retrieval-Augmented Generation (RAG) corpus comprising the Suakin architectural literature, conservation guidelines (UNESCO, ICOMOS), and the annotated element database. This agent will support conservation professionals by orchestrating multi-step workflows: element identification from uploaded images, retrieval of similar historical precedents, generation of style-consistent restoration design alternatives, and structured reporting of conservation priority assessments.

VII. ETHICAL CONSIDERATIONS AND COMMUNITY ENGAGEMENT

The deployment of AI systems in the documentation and revitalization of indigenous and post-colonial heritage sites requires careful attention to ethical dimensions that extend beyond technical performance metrics.

7.1 Cultural Sensitivity and Representational Equity

Training AI models on heritage imagery necessarily encodes particular cultural perspectives and aesthetic judgments. For Suakin, a site embedded in Islamic architectural tradition and Sudanese cultural identity, it is essential that dataset curation, annotation taxonomy, and model evaluation criteria are developed in genuine partnership with Sudanese architectural historians, local community representatives, and heritage professionals rather than imposed by external research teams. Participatory annotation workshops and community validation of model outputs are proposed as mandatory components of the research protocol.

7.2 Data Sovereignty and Privacy

All imagery, documentation, and derived datasets generated through this project will be subject to data governance agreements developed with Sudanese heritage institutions (the National Corporation for Antiquities and Museums of Sudan, NCAM) establishing community ownership of the data and requiring institutional approval for external use. Special care will be taken regarding the documentation of inhabited spaces in Al-Qeyf to protect residents' privacy.

7.3 Conflict Context Sensitivity

Sudan's ongoing civil conflict (which escalated dramatically in April 2023 and has continued to affect heritage sites including Suakin) creates urgent motivation for AI-assisted remote documentation while simultaneously imposing operational constraints on fieldwork. The research team will adhere to conflict-sensitive research protocols, avoiding data collection activities that could endanger local collaborators, and will coordinate with humanitarian organizations operating in eastern Sudan.

7.4 Risk of AI Hallucination in Heritage Contexts

Generative AI models, including LLMs and image generation systems, are known to produce plausible-looking but historically inaccurate outputs. In heritage conservation, such hallucinations could lead to incorrect restoration decisions with irreversible consequences. All generative model outputs proposed in this paper are therefore positioned explicitly as decision-support tools requiring expert architectural review, not as authoritative restoration specifications. Model limitations and uncertainty quantification will be transparently communicated in all conservation reports generated by the proposed AI agent.

VIII. PRELIMINARY RESULTS FROM ANALOGOUS HERITAGE CONTEXTS

While no results from a Suakin-specific model are yet available, the following summary of performance achieved in architecturally analogous heritage contexts provides a calibrated expectation of what the proposed pipeline can achieve upon dataset assembly:

Heritage Context	Task	Model	Performance	Relevance to Suakin
Indonesian vernacular houses (5 types)	Building type classification	CNN + SVM	96.7% accuracy	Multi-typology classification
Architectural Heritage Elements dataset (10 classes)	Element-level recognition	DenseNet121 + NASNetMobile	95.56% accuracy	Element classifier benchmark
Chinese historical buildings	Style classification	Swin Transformer	>97.8% F1	Regional style classification

Gulang Island, China (UNESCO)	Damage defect detection	Swin+YOLOv5	99.2% / mIoU 92%	Condition assessment
Khartoum (Sudan)	Building extraction from satellite	Mask R-CNN	AP@.50:.95 = 71.9	Direct Sudanese context
Iranian historic buildings	Style/type classification	MobileNetV2+ResNet	F1 ~94%	Islamic architecture transfer
Chinese diaspora architecture	Style classification + retrieval	CNN+Attention / CLIP+SVM	98.3% / mAP 76.6%	Multimodal retrieval pipeline
Conflict-zone monuments (Gaza/Iraq/Ukraine)	Period/type/location classification	Multi-CNN ensemble	94.52% accuracy	Conflict-site heritage AI

Table 3: AI Performance Benchmarks from Architecturally Analogous Heritage Contexts

These results collectively indicate that — with an appropriately constructed and labeled Suakin dataset — element-level classification accuracies of 90–98% and building-level style classification accuracies of 93–97% are achievable targets. Condition assessment and damage detection models are similarly feasible, with the Gulang Island precedent (a UNESCO island heritage site with coral-stone analogy in material fragility) being particularly instructive.

IX. RESEARCH GAPS AND FUTURE DIRECTIONS

This review and proposal identifies the following critical research gaps requiring targeted attention:

Research Gap	Proposed Action	Priority
No labeled image dataset for Suakin or eastern Sudan	UAV + ground survey + archive digitization campaign	Critical
No AI classifier for Suakin architectural elements	Transfer-learning CNN pipeline (this paper)	High
No generative restoration model for coral-stone architecture	Conditional GAN / diffusion model trained on Red Sea typologies	High
No LLM agent for Sudanese heritage conservation	ArchGPT-style agent with RAG corpus from Suakin literature	Medium
No community-participatory AI protocol for Sudan	Participatory annotation workshops with NCAM	High
No 3D point-cloud semantic segmentation for Suakin	Terrestrial LiDAR / photogrammetry + 3D CNN segmentation	Medium
No quantitative condition-assessment model	Degradation regression model from multi-epoch imagery	Medium

Table 4: Identified Research Gaps and Proposed Actions for AI-Based Suakin Heritage Research

Future work will focus on executing the data collection campaign described in Section 4.2, establishing formal institutional partnerships with NCAM, the University of Khartoum Faculty of Architecture, and international heritage bodies, and publishing the first publicly available annotated dataset of Suakin architectural imagery to support the global heritage AI community.

X. CONCLUSION

Suakin Island represents a heritage emergency: a site of extraordinary architectural and cultural significance facing irreversible loss without urgent documentation, analysis, and conservation intervention. This paper has argued, on the basis of a comprehensive review of current AI capabilities and a detailed methodological proposal, that Large AI Models — encompassing deep learning classifiers, generative models, LLM reasoning agents, and multimodal retrieval systems — offer transformative tools for the revitalization of Suakin's built heritage.

We have demonstrated that analogous heritage contexts, from UNESCO island sites in China to Islamic architecture in Iran and vernacular buildings across Asia, have already achieved classification accuracies of 90–98% using the proposed methods. We have outlined a complete four-stage pipeline tailored to Suakin's specific challenges: data scarcity, conflict-affected access, material uniqueness, and cultural sensitivity requirements. We have further identified the ethical imperatives — community participation, data sovereignty, and transparent communication of model limitations — without which AI tools cannot be responsibly deployed in heritage contexts.

The path forward requires collaborative effort across disciplines and borders: Sudanese architects, historians, AI researchers, heritage conservation professionals, and local community stakeholders must work in concert to build the foundational data infrastructure and culturally grounded models that will enable AI to serve as a genuine partner in preserving Suakin for future generations. The parametric shape grammar established by AbdulRaheem Bolaji and Rayis (2016) stands as the essential computational foundation upon which this AI-driven revitalization framework is built \u2014 its formal vocabulary of spaces, adjacency rules, and dimensional parameters providing both the architectural knowledge base and the feature ontology for the machine-learning models proposed in this paper. This paper is offered as a comprehensive roadmap for advancing that pioneering work into the era of large AI models.

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Declarations

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