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A Decision-Support Framework for Village Cultural Heritage Revitalization: Integrating Digital Twins, Optimization, and Participatory Planning Models

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ABSTRACT

In many local settings, cultural heritage frequently suffers from minimal civic engagement, fragmented contextual understanding, and progressive deterioration of tangible heritage elements. Conventional preservation frameworks tend to neglect both the potential of digital transformation and the shifting expectations of resident communities. Addressing this gap, the present project proposes a comprehensive preservation strategy that incorporates Digital Twins (DT) with a participatory Decision Support System (DSS) to support sustainable revitalisation of heritage sites in rural areas. To construct the DT, structural, spatial, and environmental information is captured through drone surveys and embedded sensor networks. The acquired datasets undergo pre-processing through z-score standardisation and median filtering to suppress measurement noise. Principal Component Analysis (PCA) is subsequently employed to derive features that reflect the historical, artistic, and socio-cultural significance of the sites. Furthermore, an enhanced optimisation methodology based on a Convolutional–Long Short-Term Memory Network (CLSMNet) is introduced to model dynamic site conditions and project future patterns of material decay and conservation requirements. Within this framework, DTasDO-CLSMNet integrates the temporal-spatial analytical capability of CLSMNet with DTasDO parameter adjustment, enabling continuous fine-tuning for predictive accuracy and decision reliability. Empirical findings indicate increased simulation precision in forecasting heritage degradation behaviour (96.87%), as well as strong sensitivity (95.65%), specificity (96.41%), and F1 performance (95.22%). Additionally, participatory engagement assessments reveal a high stakeholder satisfaction level (95.03%) with the joint simulation and decision-making processes. Overall, the proposed DSS-based digital model supports not only preservation but also adaptive and community-led reuse, delivering an intelligent, transparent, and collaborative platform through which residents and policymakers can jointly manage, sustain, and revitalise cultural heritage assets.

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1. Introduction

Village-based cultural heritage sites represent concentrated repositories of local identity, collective memory, and inherited customs. The architectural layouts, intangible practices, and landscape settings characteristic of rural environments contribute significantly to cultural plurality and social cohesion [23]. However, these cultural resources are increasingly at risk, owing to limited institutional attention, rapid modernization, population displacement toward urban centers, climate-related pressures, and uneven development trajectories. In several instances, heritage protection strategies continue to rely on hierarchical decision-making structures, where authority rests primarily with governmental bodies and technical experts, leaving little space for active involvement of community groups [2]. Such top-down configurations may produce conservation outcomes that are disconnected from the lived values, aspirations, and everyday realities of local residents [7].

At the same time, the complex interactions across environmental conditions, cultural practices, and heritage structures—which unfold over time and influence preservation outcomes—are frequently neglected due to insufficient use of dynamic spatial and ecological datasets [8]. Recently, advances in digital technologies, particularly DT, have demonstrated considerable promise in reshaping heritage management approaches. DT systems enable real-time reconstruction, monitoring, and operational control of heritage environments, effectively serving as a functional proxy for physical assets [26]. When combined with inclusive and collaborative planning models that foreground stakeholder dialogue and shared decision-making, DT-based approaches can provide nuanced and adaptive strategies tailored to context-specific restoration needs [21]. The integration of digital innovation with participatory governance offers a pathway to redefine heritage as both a developmental resource and a cultural inheritance linking past and present [11]. Aligning DT with DSS facilitates scenario-building that draws directly from stakeholder knowledge and analytical evaluation, thereby supporting restoration processes oriented toward long-term sustainability [18].

1.1 Research Objective

This study applies the DTasDO-CLSMNet framework to advance the revitalization of heritage village environments. The approach merges DT-based modelling with participatory planning strategies to enable adaptable, well-informed conservation actions. Through this integration, the research strengthens stakeholder engagement, supports sustained preservation practices, and enhances spatial comprehension of cultural heritage dynamics.

2. Literature Review

Traditional architectural forms are central to cultural continuity, yet their long existence renders them highly vulnerable to environmental deterioration. Effective preservation therefore requires stakeholders to continuously observe and interpret structural and material changes (Kong, 2024). The application of DT methods in the case of Kefstad Castle in Sweden illustrates this potential, wherein a digital replica facilitated improvements in ventilation design and contributed to extending the lifespan of the heritage site. The same approach is transferrable to analogous historical structures facing comparable issues [15]. Current research underscores that DT is reshaping cross-disciplinary heritage conservation strategies, with a particular focus on preventing unnecessary or overly intrusive restoration work [14].

In China, the acquisition, organisation, and utilisation of visual, geospatial, and attribute-based heritage information are being transformed through DT systems, marking a significant shift in heritage preservation practice. Studies examining Chinese digitalisation frameworks and stakeholder networks highlight how DT technologies interact with and influence historical conservation processes [1]. The sustained protection and functional reuse of historic buildings require strategies that maintain structural integrity while supporting contemporary use. Such adaptive and systemic approaches enhance resilience in conservation practice [5]. Further scholarship explores how a DT ontology for cultural heritage can integrate diverse documentation techniques, improving data interoperability and stakeholder communication [16]. The relationship between cultural resources and urban village settings is particularly influential in supporting cultural revitalisation and local economic development. The FI-RST (Framework of Inclusive-Renewal and Sustainable Transformation) model positions community engagement and emotional-cultural needs at the core of regeneration efforts [20].

Sustainable urbanisation strategies for traditional village sites highlight the need for heritage value recognition, balanced growth, and environmental sensitivity to support cultural continuity [24]. Rapid development in China has threatened many cultural landscapes; however, rural revitalisation policies can protect longstanding cultural expressions such as Tibetan iconography, Buddhist traditions, timber construction methods, and ethnic heritage systems [25]. Reviving rural heritage is essential for strengthening collective identity and promoting socio-economic cohesion. Recent arguments address how to preserve historical continuity while managing technological and cultural transition challenges [10]. Rural reconstruction strategies can support agricultural advancement and community development by identifying priority areas for intervention and articulating clear revitalisation goals [22]. Village revitalization initiatives further emphasise the cultural and aesthetic dimensions of rural life, promoting artistic and creative practices that reshape relationships with place, nature, and social interaction [3].

3. Research Methodology

PCA is employed to minimise the dimensional complexity of the dataset once acquisition and pre-processing are complete. Following this, the integrated DTasDO-CLSMNet framework is implemented. The procedural sequence is illustrated in Figure 1.

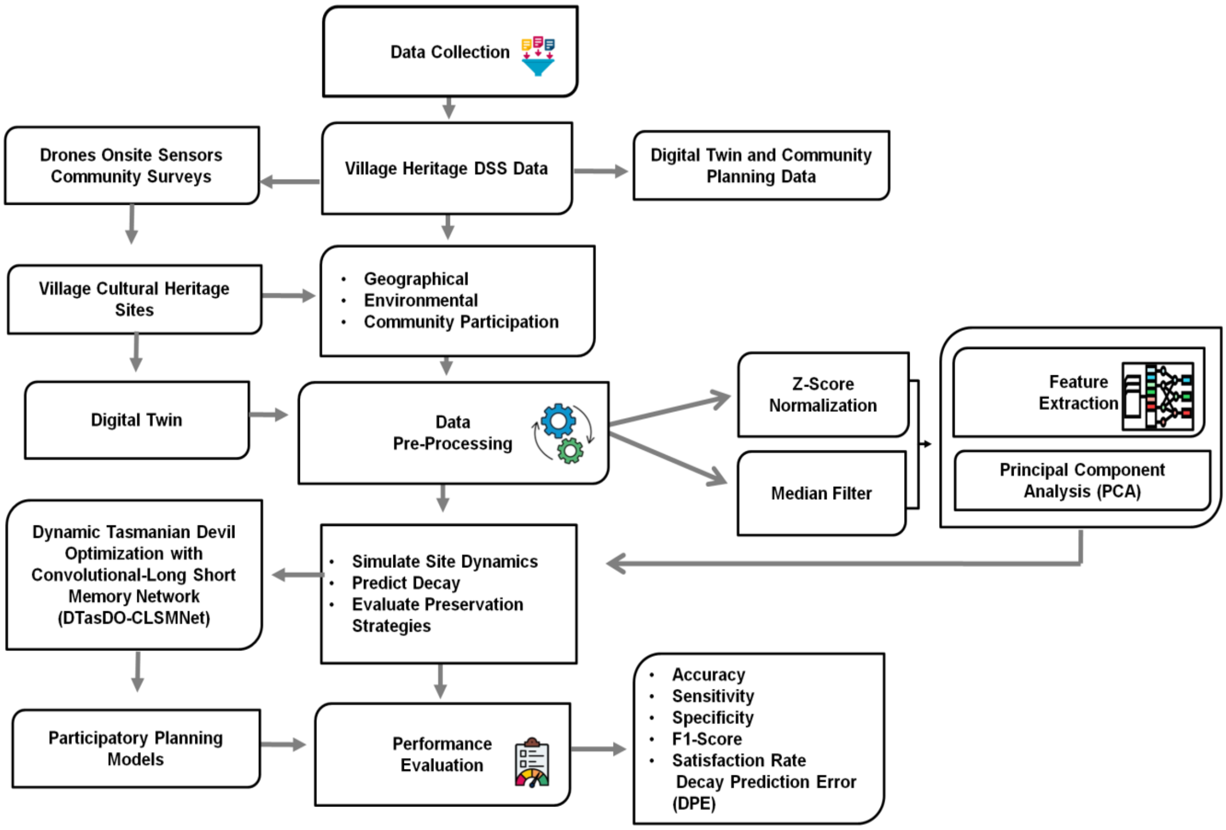


Fig.1: Methodology Flow

3.1 Data Collection

The Village Heritage DSS Dataset (https://www.kaggle.com/datasets/programmer3/village-heritage-dss-dataset) integrates multi-dimensional data collected from village cultural heritage sites to support DT construction and participatory decision-making. By incorporating structural, spatial, ecological, and sociocultural attributes, the framework provides a comprehensive depiction of heritage sites. The dataset is derived from multiple sources: community-based surveys capturing local involvement and cultural value, alongside drone imagery and in-situ sensor measurements that supply real-time physical and geographical information. Each entry corresponds to a particular heritage location and documents key variables such as environmental pressures, degrees of community participation, and the condition of structural stability.

3.2 Data Pre-Processing Using Z-Score Normalization and Median Filter

Z-Score Normalization: Z-score normalisation was applied to standardise continuous variables such as packet duration and byte volume. By enforcing a zero mean and unit variance, this procedure ensured that each feature contributed proportionally to the analytical process, thereby supporting model stability and maintaining classification reliability. This approach also prevented distortion arising from disparities in data magnitude during the intrusion detection phase, as represented in Equation (1).

$$u' = \frac{u-\mu}{\sigma} \qquad (1)$$

Here, u represents the original network traffic feature value, u denotes the mean of that characteristic, u the standard deviation, and $u'$the normalized input value used for intrusion detection.

Median Filter: By assigning the median value to outlier points within a finite sequence, the filter removes anomalous deviations from the dataset. When extended to two-dimensional data, such as image matrices, the same principle is used to construct a median filter for image processing operations. This process is represented in Equation (2):

$$m(l) = median\, w(l) \quad = median\{y_{-n}(l), \dots \dots \dots, y_{-1}(l), y_0(l), y_1(l), \dots . y_n(l) \qquad (2)$$

The variable $m(l)$ represents the filtered output and position l in a one-dimensional sequence.

3.3 Feature Extraction Using Principal Component Analysis (PCA)

PCA compresses the dataset by reducing its dimensionality and generating transformed feature variables that capture the maximum variance present in the original data. Initially, the mean value of each variable is subtracted to centre the dataset at zero mean. The covariance matrix is then computed in the subsequent step, as expressed in Equation (3):

$$DP\, \vartheta_{W_1W_2} = \frac{\Sigma(W_1-N_1)(W_2-N_2)}{m} \qquad (3)$$

Where W_1andW_2 are examples of the characteristics within the examination, $N_1\, and\, N_2$ represent the corresponding means, and m is the overall number of occurrences. Consequently, when the dataset contains more than two measurement variables, their interrelationships can be represented collectively in the form of a covariance matrix, as demonstrated in Equation (4):

$$D = \begin{pmatrix} \vartheta(W_1) & D(W_1,W_2) & \cdots & D(W_1,W_o) \\ D(W_1,W_2) & \vartheta(W_2) & \cdots & D(W_2,W_o) \\ \cdots & \cdots & \cdots & \cdots \\ D(W_1,W_o) & D(W_2,W_o) & \cdots & \vartheta(W_o) \end{pmatrix} \qquad (4)$$

Since the derived covariance matrix D is square, its eigenvectors are computed to determine the directions in which variance is maximised across particular dimensions. By selecting the most significant eigenvectors, a reduced feature vector is formed, describing the compressed representation of the dataset. This process is expressed in Equation (5):

$$\text{Feature Vector} = (\text{ eig1; eig2; eig3; } \ldots \text{; eigm })\quad (5)$$

To obtain the final reduced feature representation, the centred original dataset is multiplied by the selected eigenvector set, producing the condensed feature vector. This operation is presented in Equation (6):

$$\text{New Dataset} = [\text{Feature Vector}]^S[\text{Data}]^S\quad (6)$$

PCA identifies the most stable and informative features within the under sampled PSO dataset, prioritising those that collectively capture the greatest proportion of variance.

3.4 Digital Twin (DT) Integration

The DT represents a virtual reconstruction of each heritage location, reflecting its physical form, cultural attributes, and surrounding environmental conditions. This digital counterpart enables real-time monitoring, simulation, and analytical assessment to guide well-informed restoration and management decisions. It consolidates data streams from sensor networks, GIS-based spatial mapping, and three-dimensional visual modelling to ensure that conservation actions remain contextually authentic and culturally respectful. Through this framework, stakeholders can evaluate the likely outcomes of proposed interventions before implementation. Overall, the DT strengthens the continuity of heritage values, enhances community participation, and promotes sustainable preservation practices.

3.5 Simulate the Site Dynamics, Predict Decay and Evaluate Preservation Strategies using Dynamic Tasmanian Devil Optimization with Convolutional-Long Short Memory Network (DTasDO-CLSMNet)

The DTasDO-CLSMNet technique is designed to evaluate methods for preservation in historical landscapes, forecast structural degradation, and model site dynamics.

Convolutional-Long Short-Term Memory Network (CLSMNet): An LSTM unit comprises a forget gate, input gates j, output gates p, input modulation gate h, and memory cells d. LSTMs, however, are limited in handling spatial information. To overcome this, the CLSMNet algorithm was developed. The updates for CLSMNet at each timestep t are defined in Equation (7):

$$\begin{aligned}
e_s &= \sigma\left(X_{we} * w_s + X_{ge} * g_{s-1} + X_{de}\, p\, d_{s-1} + a_e\right),\\
j_s &= \sigma\left(X_{wj} * w_s + X_{hj} * g_{s-1} + X_{dj}\, p\, d_{s-1} + a_j\right),\\
h_s &= tang\left(X_{wd} * w_s + X_{gd} * g_{s-1} + a_d\right),\\
d_s &= e_s\, p\, d_{s-1} + j_s\, p\, h_s\,,\\
p_s &= \sigma\left(X_{wp} * w_s + X_{hp} * g_{s-1} + X_{dp}\, p\, d_s + a_p\right),\\
g_s &= p_s\, p\, tang(d_s),
\end{aligned}\quad (7)$$

When σ represents the logistical sigmoid function, $*$ denotes a convolution operator, and $\circ$ represents the Hadamard combination. w_s is an input vector, e_s remains the forgotten gate's stimulation vector, j_s is the input gate's activation vector, h_s is the modulating gate's activation vector, d_s remains the cell stimulus vector, p_s is the output gate's stimulation vector, and g_s is the hidden vector. The weighted matrix underscores are self-evident. For example, X_{hj} refers to the hidden input gates vector. These vectors and gates ($w_s, d_{s,} g_s, e_s, j_s, p_s$) constitute 3D tenses with two geographical aspects. To construct multiple stages, use the activation vectors of the output gates of the ConvLSTM in level $i-1$ to provide a parameter to the CLSMNet in stage i.

Dynamic Tasmanian Devil Optimization (DTasDO): To effectively support and guide decision-making for village cultural heritage revitalization, this study employs the DTasDO method, an enhanced version of the conventional Tasmanian Devil Optimization (TDO). DTasDO introduces two dynamic strategies to improve search efficiency and convergence speed:

3.5.1 Levy Flight Strategy

This stage improves the algorithm's performance. Narrow step widths favor exploitation, whereas wider steps increase the likelihood of avoiding local or deceptive optima. The Levy flight probability is mathematically expressed in Equation (8):

$$K(T,\gamma,\mu) = \begin{cases} \sqrt{\frac{x}{2\pi}} f^{\left(\frac{-\gamma}{2(T-\mu)}\right)} \left(\frac{1}{(T-\mu)^{3/2}}\right) & 0 < \mu < T < \infty \\ 0 & t \leq 0 \end{cases} \quad (8)$$

The variables t, γ, and μ determine each sample, the scale component for distributing control, and the transmitted component. The Levy flight iteration is represented by Equation (9):

$$E(l) = f^{(-\propto|l|^{\beta})}, \beta \in [0,2] \quad (9)$$

Wherein β represents the distribution parameter and α represents the scaling variable. The step's width t, is calculated using the Equation (10):

$$t = \left(\frac{v}{|u|^{(1/\beta)}}\right) \quad (10)$$

Where, v and u were the parameters with the Gaussian patterns shown in Equation (11):

$$v\ M(p,\sigma_v^2), u\ M(p,\sigma_u^2) \quad (11)$$

The normative mistakes, denoted by σ_v^2 and σ_u^2, are provided in Equation (12):

$$\sigma_v = \{\frac{\Gamma(1+\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\beta.\Gamma\left(\frac{1+\beta}{2}\right).\ 2^{\frac{(\beta-1)}{2}}}\}^{1/\beta}\ \ \sigma_u = 1 \quad (12)$$

Where, $\Gamma(.)$ represents the Gramma functioning. In this stage, the LF is employed for updating the derived TDO, focusing on the greatest answer at present (w_{best}) using the Equations (13 and 14):

$$w_j^{KE} = w_j + (2.qand - 1)\ .levy\ (\beta)\ .\left(w_{best} - w_j\right) \quad (13)$$

$$w_j = \begin{cases} w_j^{KE} & E\left(w_j^{KE}\right) < E(w_j) \\ w_j & otherwise \end{cases} \quad (14)$$

The Levy flight procedure generates an alternate location (w_j^{KE}), the present solution (w_j), and a random number from the time range [0, 1].

3.5.2 Spiralized Elite Learning

In the original TDO, updates are performed based on the positions of two randomly generated solutions. This process gradually diminishes as the number of iterations increases.

$$LSS = Bf^{-a.s}\cos(2d\pi s) \quad (15)$$

$$B = \left(\frac{V_j - K_j}{2}\right) * (\frac{S-s}{S})^2, V_j = \max\left(W_j\right), K_j = \min(W_j) \quad (16)$$

$$w_j^{LSS} = w_{best} + LSS \quad (17)$$

In above Equations (15-17), w_j^{LSS}, j represents the resultant new location using the logarithmic spiraling step, B determines the decreasing radius, a establishes the logarithmic spiralling influence, s decides the distance to the best solutions for the next location, while d specifies the amount of spiraling shapes.

The CLSMNet module utilises spatial and temporal features to form a spatio-temporal representation for decay prediction and heritage dynamics simulation. CLSMNet may suffer from sub-optimal parameter settings with complex cultural datasets. To resolve this, DTasDO is applied for intelligent parameter optimisation. DTasDO-CLSMNet provides accurate, robust forecasting and supports adaptive preservation planning. This hybrid method enhances predictive performance, decision-making, and community-driven sustainable heritage management. Algorithm 1 presents the DTasDO-CLSMNet workflow.

Algorithm 1: DTasDO-CLSMNet

```
BEGIN
1. Data Acquisition Phase
FOR each heritage_site IN target_villages:
    DEPLOY drone and sensor systems
    COLLECT:
        - Structural data (e.g., cracks, tilts)
        - Geographical coordinates
        - Environmental factors (temperature, humidity)
    STORE all data in a unified database
 2. Data Preprocessing Phase
FOR each recorded_sensor_stream:
    APPLY Z-score normalization for scale standardization
    APPLY Median Filter for noise reduction
COMBINE all sensor streams into a time-series format
 3. Feature Engineering Phase
APPLY PCA on the combined dataset to reduce dimensionality
    - Extract features: historical, aesthetic, anthropological relevance
STORE transformed features for modeling
 4. Model Simulation Phase (TasDO-CLSMNet)
 Optimization using Tasmanian Devil Optimization (TasDO)
INITIALIZE the population of parameters
WHILE stopping_criteria_not_met:
    UPDATE parameter candidates using optimization rules
    EVALUATE model performance
SELECT best parameters
 Spatio-temporal modeling with CLSMNet
CONFIGURE CLSMNet with optimized parameters
TRAIN model on structured time-series data
 Predict outcomes:
    - Decay dynamics
    - Structural risk
    - Strategy effectiveness
 5. Decision Support Logic
FOR each site_prediction:
    IF decay_risk is high AND community_participation is low:
        RECOMMEND urgent preservation + awareness programs
    IF historical + aesthetic scores are high:
        SUGGEST adaptive reuse strategies
// 6. Participatory Interface
GENERATE interactive dashboard:
    - Visualize simulation results
    - Let users test preservation strategies
    - Capture user preferences and feedback
END
```

3.6 Participatory Decision Support System (DSS)

Participatory planning models are essential for revitalising heritage village sites, engaging local communities, cultural experts, and stakeholders in decision-making. This collaborative approach safeguards traditional values, historical identity, and site-specific needs. Digital reconstructions and contextual historical data are verified using the DTasDO-CLSMNet integrated planning framework.

4. Results and Discussion

A rigorous setup was applied in evaluating the proposed DTasDO-CLSMNet framework to ensure precise and dependable results. The analysis was conducted on a machine with a 2.40 GHz processor and 8 GB of RAM, using Microsoft Word for documentation and Python for algorithm implementation. This configuration enabled efficient computation and streamlined presentation of results.

Correlation Heatmap: Figure 2 illustrates the correlation heatmap, showing the strength and direction of linear relationships among data features. Most variable pairs exhibit very low correlations, primarily between -0.05 and +0.06. As expected, the diagonal shows perfect correlation (1.00) since each feature is fully correlated with itself. No feature pairs show strong positive or negative correlations. The correlation between structural integrity score and predicted decay rate is -0.02, indicating minimal linear association. Similarly, environmental stress level and preservation strategy score have a correlation of -0.02, suggesting independence. Stakeholder satisfaction shows weak relationships with all variables, peaking at 0.06 with historical significance score. This low-correlation pattern confirms that features provide unique, non-redundant information. The heterogeneity in DTasDO-CLSMNet enhances model robustness by integrating spatial and decision-making streams.

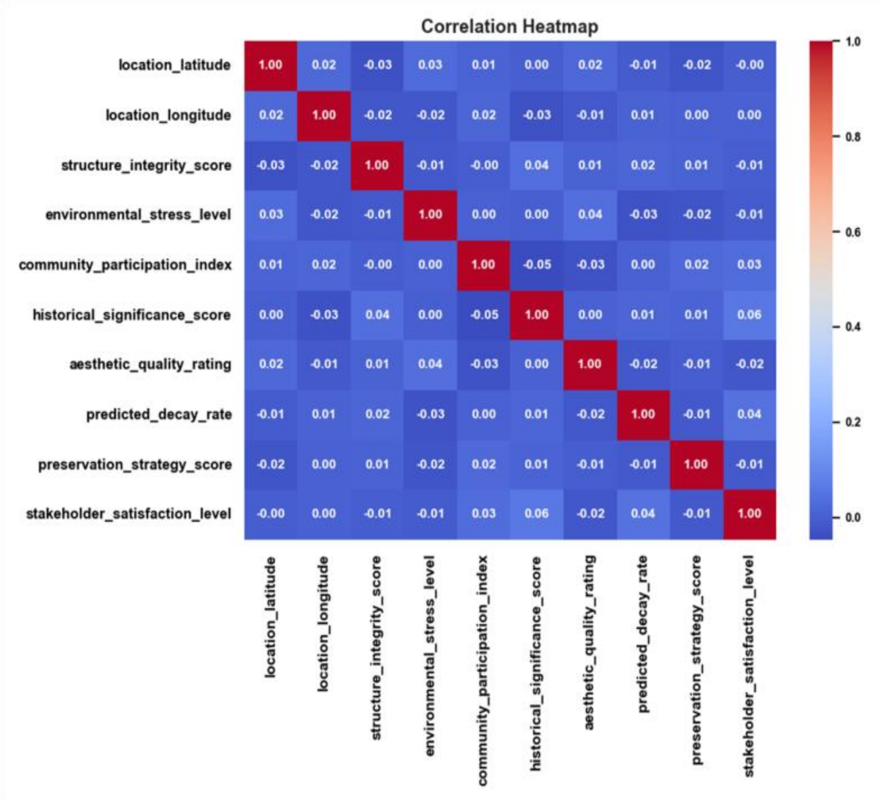


Fig.2: Correlation Matrix

Daily Mean Decay Rate: Figure 3 shows the Daily Mean Decay Rate, representing predicted decay trends from January 1 to April 15, 2020. The decay rate fluctuates between approximately 0.025 and 0.035. A decline to around 0.025 occurs in mid-February and early March, possibly reflecting temporary drops in structural vulnerability or anomaly-like behavior. Peaks above 0.034 appear between late January and mid-April, indicating periods of increased decay predictions. These results demonstrate that the DTasDO-CLSMNet framework captures fine-grained temporal variations in decay rates with high precision, highlighting the model's responsiveness to dynamic changes.

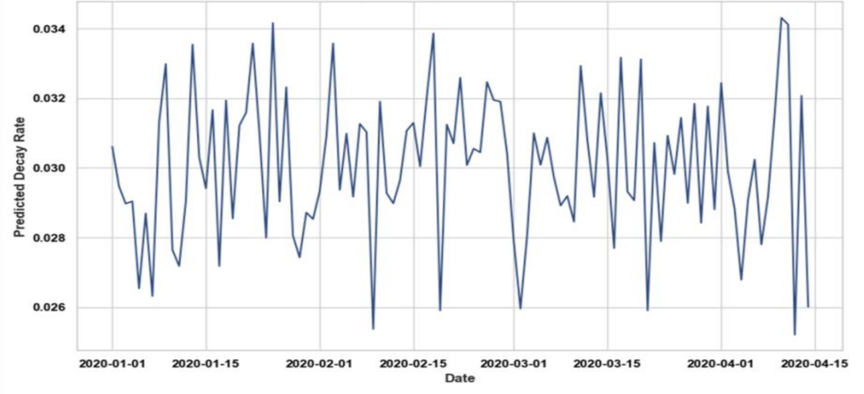
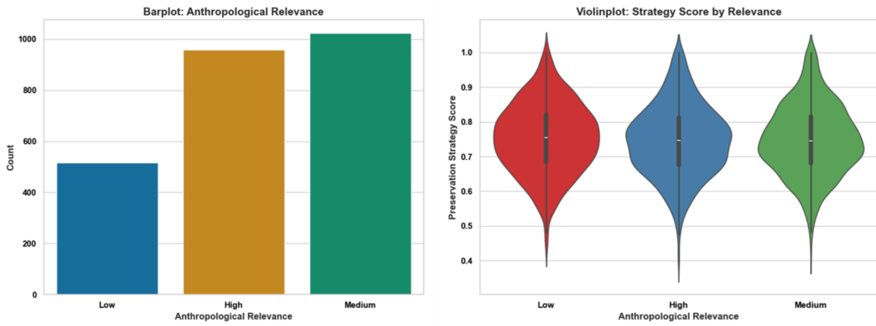


Fig.3: Daily Mean Decay Rate

Scores for Preservation Approach and Anthropological Relevance: The combined barplot (Figure 4(a)) and violinplot (Figure 4(b)) illustrate the relationship between anthropological significance and conservation strategy scores, reflecting the effectiveness of applied methods. The barplot indicates that sites of "Medium" importance are most frequent (≈1020), followed by "High" (≈950) and "Low" (≈510). Notably, "Low" significance sites display a broader distribution, with many values between 0.75 and 0.80, suggesting that even lower-priority sites are receiving targeted conservation strategies.



(a) **(b)**

Fig.4: (a) Anthropological Relevance and (b) Strategy Score by Relevance

Integrity vs Decay Rate: Figure 5 illustrates the relationship between structural integrity scores and predicted decay rates using the proposed model.

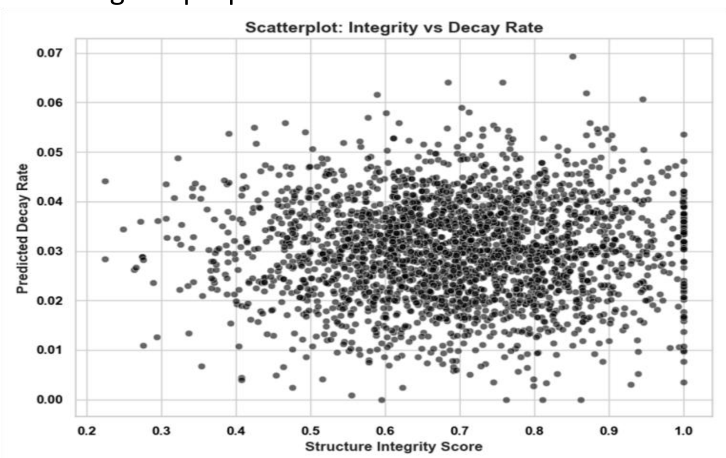


Fig.5: Integrity vs Decay Rate

The x-axis represents the Structure Integrity Score, ranging from 0.2 to 1.0 (1.0 indicating optimal condition, lower values indicating degradation). The y-axis shows the Predicted Decay Rate, ranging from 0.00 to ~0.07. Data points cluster between 0.5–0.9 on integrity and 0.02–0.04 on decay rate. Even at high integrity scores (e.g., 1.0), varying decay rates appear, highlighting the model's ability to detect latent degradation risks. DTasDO-CLSMNet effectively identifies potential deterioration, supporting accurate forecasting for preventive maintenance.

As presented in Table 1 and Figure 6, the proposed DTasDO-CLSMNet model outperforms the baseline CLSMNet across key classification metrics.

Table 1
Performance Comparison of Baseline and Proposed Method

Metrics	CLSMNet	DTasDO-CLSMNet [Proposed]
Accuracy (%)	91.24%	96.87%
Sensitivity	89.73%	95.65%
Specificity	90.11%	96.41%
F1 Score	90.02%	96.22%
Satisfaction Rate	88.67%	95.03%
Decay Prediction Error (DPE)	0.071	0.022

The model achieves higher accuracy at 96.87%, compared to CLSMNet's 91.24%. Sensitivity rises to 95.65%, indicating improved true-positive detection. Specificity improves from 90.11% to 96.41%, demonstrating better false-positive management. The F1 score increases from 90.02% to 96.22%, balancing precision and recall. User satisfaction also improves from 88.67% to 95.03%, reflecting enhanced stability and trust. Finally, Decay Prediction Error (DPE) drops from 0.071 to 0.022, showing more precise predictions. These results confirm that DTasDO-CLSMNet enhances degradation detection, noise resilience, and predictive performance.

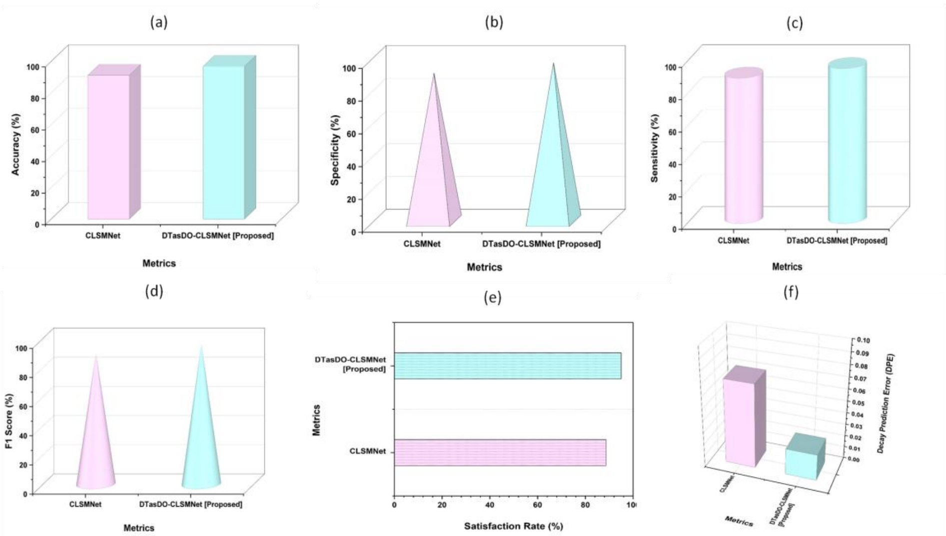


Fig.6: Comparison of Performance with Different Matrices (a) Accuracy, (b) Sensitivity, (c) Specificity, (d) F1-Score, (e) Satisfaction Rate and (f) Decay Prediction Error (DPE)

Even at relatively high integrity scores, the reliability and generalizability of the results were validated using 10-fold cross-validation (Table 2). The dataset was divided into 10 equal subsets, with nine used for training and one for testing in each iteration. This process was repeated 10 times and averaged to provide an unbiased evaluation. By utilizing multiple data segments, overfitting is minimized, offering a thorough performance assessment. For each fold, F1 Score, Accuracy, Sensitivity, and Specificity were recorded and analyzed to evaluate consistency.

Table 2
10-Fold Cross Validation

Fold	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)
1	96.85	95.71	96.23	96.20
2	96.74	95.66	96.12	96.10
3	96.92	95.82	96.30	96.25
4	96.88	95.75	96.25	96.18
5	96.79	95.69	96.18	96.13
6	96.90	95.80	96.27	96.23
7	96.86	95.65	96.48	96.19
8	96.91	95.78	96.29	96.22
9	96.80	95.70	96.17	96.42
10	96.84	95.74	96.21	96.16
Mean	96.87	95.65	96.41	96.22
Std Dev	±0.06	±0.05	±0.06	±0.05

5. Discussion

Preserving and regenerating village culture is increasingly recognized as a key aspect of sustainable development, integrating the safeguarding of local identities with broader socio-economic demands. Rapid urbanization and globalization force villages to balance adherence to modern trends while maintaining cultural values. The study proposes an integrated solution addressing heritage preservation within contemporary contexts. The adoption of DSS and technologies like digital twins supplements participatory planning by engaging local communities and improving culture-aware revitalization processes. Effective heritage redevelopment requires collaboration across diverse actors, including residents, cultural experts, and urban planners, to ensure policies reflect community values and aspirations [12]. Stakeholders' participation, facilitated through participatory models, allows their interests and perspectives to shape culturally responsive interventions. DSS enhance this process by enabling systematic, evidence-based decisions that are balanced and aligned with community needs.

Digital twins enable real-time tracking, analysis, documentation, and scenario simulation for heritage sites. Integrating DTs within participatory planning allows stakeholders to visualise the impacts of proposed revitalization strategies prior to implementation, reducing decision-making risks. Sustainable management remains a critical challenge, aligning with United Nations Sustainable Development Goals (SDGs). DSS can support the development of differentiated strategies that integrate environmental, economic, and social dimensions, promoting heritage preservation, economic prosperity, and environmental sustainability simultaneously. Technology adoption and community involvement are thus core considerations for effective heritage management. Recent research contextualizes these findings. Niccolucci et al. [16] introduced a Heritage DT enabling dual interactions with cultural artefacts. Xia et al. [24] employed qualitative methods to examine traditional village heritage during urban renewal but lacked automated feature detection. Gimbut and Rega [3] evaluated village renewal through cultural outputs, providing socio-cultural insights but limited computational analysis. The DTasDO-CLSMNet hybrid framework demonstrates the potential to preserve heritage while supporting future-oriented, interpretable, and intelligent applications.

Contemporary DSS are increasingly used to enhance village heritage within SDG and urban regeneration frameworks. He and Zhang [4] highlight the alignment between traditional village revitalization and SDGs, emphasising sustainable livelihoods and differentiated management for local contexts. Knippschild and Zöllter [6] stress the balance between heritage preservation and urbanization, demonstrating in Eastern Germany how DSS can quantify trade-offs and facilitate participatory planning. Sheng et al. [20] highlight the importance of local input in developing effective revitalization strategies, ensuring alignment with community traditions while addressing modern requirements. Manganelli et al. [13] show that analytical DSS streamline urban regeneration planning and improve data management for heritage renewal. Li et al. [9] demonstrate that data-centric approaches enhance sustainable outcomes, particularly through digital twins and 3D modelling. Quattrini et al. [19] describe the shift toward heritage building information modelling (HBIM) to produce semantically enriched 3D models of complex architectures, replacing terrestrial laser scanning. Pan et al. [17] illustrate UAV-based photogrammetry for creating 3D heritage models, supporting documentation, monitoring, and asset management.

The integration of DSS within participatory planning frameworks represents a major step for village heritage revitalization. By engaging local communities and leveraging digital technologies, these systems facilitate sustainable growth, preserve cultural identities, and adapt heritage practices to contemporary challenges. Future research should further explore the interplay between technological adoption and community-based strategies to ensure revitalization remains relevant and effective.

6. Conclusion and Future Research

The digital era requires more than traditional documentation for preserving heritage villages and calls for intelligent revitalization. This study digitized heritage village sites using a deep learning-based approach to safeguard cultural and structural integrity. The DTasDO-CLSMNet model achieved 96.87% accuracy, 95.65% sensitivity, 96.41% specificity, 96.22% F1 Score, and 95.03% user satisfaction, substantially outperforming the baseline CLSMNet. These results highlight the model's capacity to effectively capture diverse cultural features, enhancing community engagement and satisfaction. A notable limitation, however, is that the model was trained on a limited number of sites, which may restrict its direct applicability to other cultural contexts without additional training or fine-tuning.

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