Afr. J. Lib, Arch. and Inf. Sc. Vol. 35, No. 2 (July 2025) 85-97
https://doi.org/10.5281/zenodo.17851419

Visual Storytelling in Digital Libraries: Design Strategies for Preserving and Accessing Intangible Cultural Heritage

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Abstract

The advancement of digital technologies has substantially transformed the ways in which cultural heritage is conserved, documented, and made accessible. Visualization techniques and Heritage Building Information Modelling (HBIM) provide essential tools for safeguarding both tangible and intangible heritage, while also facilitating the creation of interactive experiences. This research examines the application of visual storytelling within digital libraries, employing deep learning methods to design strategies for the preservation and accessibility of intangible cultural heritage. The proposed model is capable of processing and analysing diverse data types, including 3D scans, photographic images, textual narratives, audio-visual recordings, and other formats. Specifically, the Bacterial Colony-tuned Lightweight Convolutional with Recurrent Neural Networks (BC-LWC-RNN) framework is utilised to automate the generation of visual narratives, establishing semantic links across heritage datasets. The resulting information is integrated into HBIM environments and delivered via immersive virtual reality interfaces, enhancing user engagement and comprehension through interactive storytelling. The LWCNN component extracts critical spatial and visual features from images or 3D scans, while the RNN component captures sequential or temporal patterns present in textual or spoken narratives, enabling the construction of coherent storylines. The BC-LWC-RNN model demonstrated an identification accuracy of 98.03% for elements of intangible cultural heritage, with a precision of 97.73%, recall of 98.23%, and F1-score of 97.85%. Experimental findings indicate that this model performs with high reliability in generating meaningful visual narratives. Overall, the approach integrates deep learning with HBIM *to support the reinterpretation, preservation, and dissemination of intangible cultural heritage within digital library platforms.*

Keywords: Visual Storytelling, Digital Libraries, Intangible Cultural Heritage, Heritage Building Information Modelling (HBIM), Bacterial Colony-Tuned Lightweight Convolutional with Recurrent Neural Networks (BC-LWC-RNN), Heritage Preservation.

1. Introduction

Cultural legacy embodies the collective memory of societies, comprising both tangible assets, such as monuments, artefacts, and manuscripts, and intangible elements, including music, rituals, oral traditions, and performing arts (Bastian, 2023). A critical challenge lies in the preservation of ICH, which is inherently dynamic, non-material, and context-dependent, whereas physical heritage has traditionally been the focus of institutional conservation efforts (Hansen et al., 2022). In recent years, the advent of digital technologies has provided unparalleled opportunities for documenting, conserving, and disseminating vulnerable forms of cultural content (Siliutina et al., 2024). Digital libraries have emerged as essential resources, offering innovative methods for accessing, distributing, and analysing heritage materials beyond simple data storage (Onunka et al., 2023). Within this context, visual storytelling has become a potent tool for conveying cultural knowledge, enhancing accessibility, understanding, and emotional resonance across diverse audiences by transforming complex heritage information into engaging narratives (Podara et al., 2021). The digital environment thus offers significant potential for preserving and revitalising community traditions by simultaneously facilitating engagement and safeguarding practices (Mutibwa, 2024). Figure 1 illustrates the Digital Heritage Preservation and Storytelling Framework.

Achieving the intended outcomes necessitates design solutions that integrate cultural sensitivity with advanced computational technologies (Stephanidis et al., 2025). Deep learning approaches combined with immersive visualization and HBIM constitute the essential foundation for constructing environments where tangible and intangible heritage coexist (Lucchi, 2025). By merging narrative creation, semantic linkage of heterogeneous information, and immersive digital experiences, these methods enhance the exploration of cultural heritage for both scholars and general audiences (Zhang et al., 2025). Within digital libraries, visual storytelling provides an innovative approach for securing and accessing ICH in the contemporary era (Odularu et al., 2024). This integration of tradition with technology ensures cultural continuity, stimulates generational interest in heritage learning, and promotes awareness of diverse cultural practices globally (García-Mieres et al., 2025). Visual storytelling situates ICH within interactive digital ecosystems, reinforcing cultural practices that preserve knowledge while enabling the adaptation of traditions to evolving contexts without compromising their authenticity or significance (Del Soldato and Massari, 2024). However, the integration of deep learning with HBIM and VR demands substantial computational resources and extensive datasets, which may pose limitations in contexts characterised by cultural diversity.

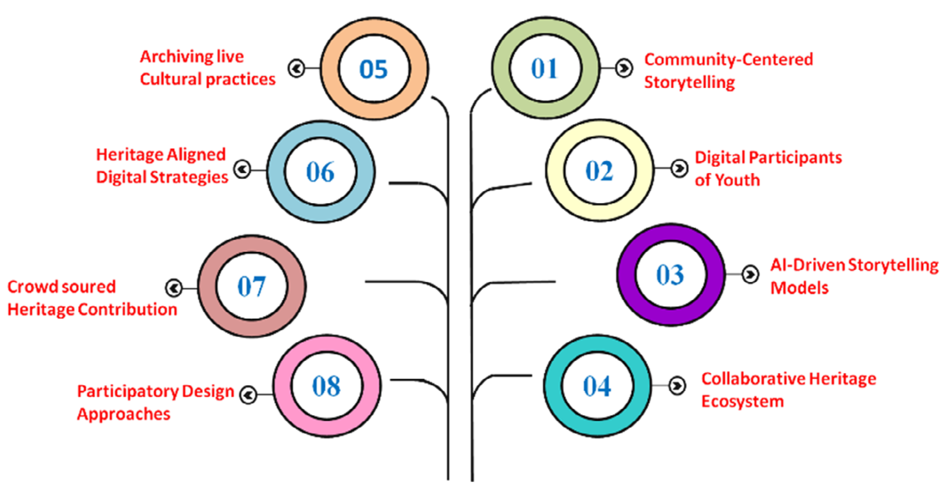

Figure 1: Digital Heritage Preservation and Storytelling Framework.

The primary objective is to develop a BC-LWC-RNN-based framework capable of facilitating interactive visual storytelling within digital libraries, thereby supporting the preservation, reinterpretation, and dissemination of intangible cultural material through the fusion of deep learning, HBIM, and immersive visualization.

1.1. Key Contributions

- Introduces a LWCNN-RNN framework optimised by BCO to generate coherent visual narratives from heterogeneous cultural heritage datasets.
- Integrates immersive VR with HBIM to facilitate participatory storytelling and safeguard ICH.
- Enhances the accuracy, efficiency, and semantic linkage of heritage data, thereby improving accessibility within digital libraries.

The structure of the paper is as follows: Part 2 provides a review of existing research on digital heritage preservation, HBIM, and deep learning methodologies. Part 3 outlines the datasets, pre-processing procedures, and details of the proposed BC-LWC-RNN model. Part 4 presents experimental results and discussion, while Part 5 concludes with principal findings and suggestions for future research.

2. Related Works

This section provides a concise overview of prior work on deep learning techniques, digital storytelling, HBIM, and cultural heritage preservation. The focus has been on innovative approaches for conserving and redesigning ICH items (Xie, 2022). By analysing modelling, ornamental characteristics, and cultural features, these approaches generate novel design atlases using AI, perceptual engineering, and form grammar, producing preliminary design concepts that integrate traditional elements with user-centred engagement to support cultural continuity. Challenges in reusing digital cultural heritage within AI include bias, insufficient data quality, and inconsistent curation (Neudecker, 2022). Leveraging libraries' expertise in preservation, metadata standards, and ethical stewardship facilitates the annotation, contextualization, and curation of datasets. Consequently, AI models benefit from enhanced, objective datasets that maintain authenticity while promoting responsible digital innovation.

UNESCO has established a comprehensive CHIS to digitally record, monitor, and conserve sites listed as World Heritage (Thekkum Kara, 2021). National CHIS initiatives address these challenges by incorporating digital archiving, mobile technologies, ICT, and visualization, enhancing the protection, recognition, accessibility, and interdisciplinary significance of cultural heritage. Digital cultural heritage datasets often raise concerns regarding provenance, bias, and heterogeneity due to multiple selection layers, incomplete documentation, and divergence from conventional machine learning datasets (Alkemade et al., 2023). Developing customised datasheets for historical institutions and adapting generic machine learning datasheets by embedding cultural heritage workflows, measures, and practices improves documentation, transparency, and dataset usability, thereby supporting ethical AI and preservation.

The heterogeneity of heritage data limits online exploration and interoperability, with few solutions integrating linked open data, web-GIS, and 3D models (Nishanbaev et al., 2021). A cloud-based web-GIS framework incorporating connected open data from GeoNames and DBpedia alongside 3D digital heritage models enables immersive exploration, access to contextual information, and expert-validated opportunities for enhanced heritage representation. Rapid societal change, economic development, and the erosion of traditional practices place ICHs at existential risk (Wang, 2022). ICH databases and digital maps employing information space theory and neural network models facilitate the recoding, reconstruction, and management of ICH, enhancing public recognition, transmission, and dissemination to support long-term preservation.

The absence of integrated knowledge systems and standardised digital descriptions hinders effective preservation, retrieval, and dissemination of ICH (Fan, 2023). Semantic Web technologies, ontology, and knowledge organisation theory support the development of conceptual models, semantic relationships, and metadata standards, enabling multi-dimensional knowledge fusion, semantic retrieval, and visualization, thus advancing digital progress and sustainable conservation of intangible cultural assets. Unrecorded natural and cultural properties threaten economic, social, cultural, and historical significance (Gireesh Kumar, 2022). To systematically preserve these assets, a unified CHIS platform is proposed to manage, document, and digitally conserve heritage while addressing operational challenges. Such a CHIS enhances visibility, sustainability, research support, tourism, and overall heritage conservation.

Energy efficiency improvements in historic buildings must preserve architectural integrity, yet asset managers often lack integrated strategies balancing performance, cost, and conservation (Massafra et al., 2022). Combining HBIM, BPS, and IFC standards, workflows for multi-criteria evaluation, model creation, and intervention testing identify optimal energy strategies, promoting sustainable preservation and the creation of shareable digital twins. Digital games as cultural heritage face deterioration and potential loss due to physical medium decay (Guay-Bélanger, 2022). The Material-Cultural Heritage Methodology, incorporating play recordings, developer and player interviews, ensures comprehensive documentation and long-term preservation of games as cultural artefacts. Confidentiality, copyright, and technological constraints restrict public access to born-digital archival collections, limiting research and study (Jaillant and Caputo, 2022). AI and machine learning, including sensitivity evaluation, identify and release non-sensitive content while automating archival tasks. Ethical considerations such as bias, transparency, and accountability are critical for responsible AI use in digital archives. Traditional knowledge protection faces challenges from misappropriation, conflicting policy interests, and potential exploitation (Fredriksson, 2022). The TKDL documents traditional medical knowledge, connecting submissions to WIPO and aligning with domestic policy objectives. TKDL supports preservation, policy implementation, and highlights tensions between strategic interests and community rights.

DH research lacks comprehensive understanding of popular topics and trends over the past decade (Joo et al., 2021). Text mining methods, including structural topic models, bigram and bi-term analyses, and keyword co-occurrence, reveal key areas such as text digitalization, linked data, cultural heritage, and semantic web, with linked open data, ontology, and social network analysis becoming increasingly central. Indigenous communities face difficulties asserting cultural identity and preserving heritage due to restricted access and postcolonial pressures (Lydon, 2021). Digital heritage programmes that digitise historical collections empower Indigenous peoples to manage, produce, disseminate, and utilise cultural materials, reinforcing communal identity and advocacy.

The preservation of traditional medical knowledge is challenged by theft and formal patent system constraints (Fredriksson, 2023). The TKDL integrates documentation theory with international patent classifications to safeguard, update, and systematise traditional medical knowledge, balancing conventional and formal systems while mitigating risks of misappropriation. Traditional libraries face challenges in accessibility, preservation, and global knowledge sharing, necessitating advanced technologies for information management (Khan, 2021). By integrating distributed databases, information retrieval, hypertext, and multimedia, digital libraries enhance global storage, retrieval, and dissemination of academic, research, and cultural materials, overcoming geographical barriers and supporting preservation. Cultural heritage research and protection are hindered by access, interpretation, and preservation challenges (Stojanović and Čajić, 2024). AI methods, supported by expert collaboration, evaluate, interpret, and restore textual and visual artefacts, improving heritage analysis while requiring ethical oversight to ensure responsible outcomes. The Fifth Industrial Revolution presents challenges for libraries to adapt to rapid technological change while addressing digital inclusion, privacy, and ethics (Adigun et al., 2024). Through interpretative content and document analysis, the integration of AI, IoT, and cloud computing is evaluated to balance ethical considerations with innovation, positioning libraries as critical actors in education, research, and community engagement.

2.1. Problem Statement

The HBIM–BPS workflow's emphasis on specific listed buildings, coupled with its dependence on accurate IFC data, may restrict its scalability, adaptability, and broader applicability across diverse historic structures (Massafra et al., 2022). Similarly, while TKDL mitigates patent misuse, its integration with formal patent systems can lead to decontextualization, diminish cultural authenticity, and marginalize indigenous ownership (Fredriksson, 2023). To address these limitations, the BC-LWC-RNN approach was employed to facilitate high-performance, inclusive, and effective heritage representation, enabling TKDL to maintain cultural context while ensuring scalability and adaptability across varied heritage architectures.

3. Methodology

The methodology integrates immersive visualization, HBIM, and deep learning to support the preservation of ICH. Heterogeneous datasets, including 3D scans, images, textual narratives, and audio recordings, are initially collected and pre-processed through feature extraction and tokenization. RNN captures sequential patterns in textual and auditory data to construct coherent narratives, while LWCNN extracts spatial and visual features from images and 3D models. Model parameters are optimised using BCO to enhance accuracy and performance. The processed outputs are incorporated into HBIM environments and visualized via VR interfaces, enabling interactive visual storytelling and heightened user engagement. Figure 2 illustrates the framework for Visual Storytelling in ICH Preservation.

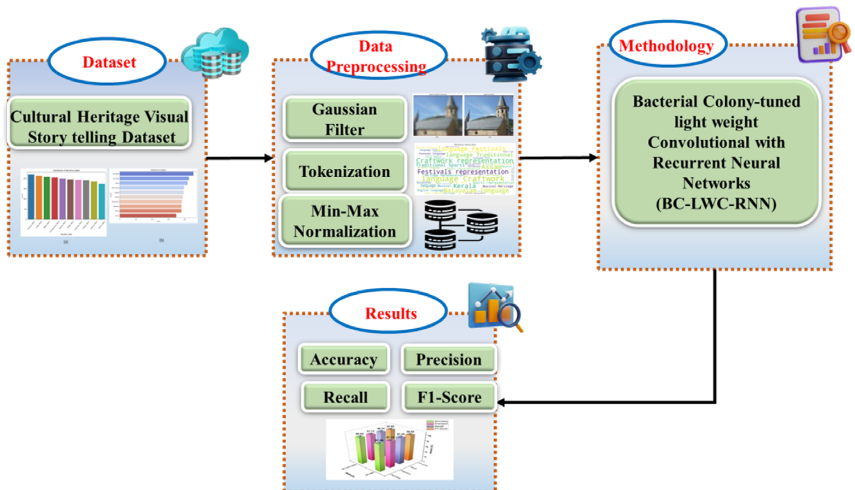

Figure 2: An Overview of the Framework for Visual Storytelling Intangible Cultural Heritage Preservation.

3.1. Dataset

The cultural heritage visual storytelling dataset was sourced from Kaggle. Designed to support the preservation, accessibility, and reinterpretation of ICH through digital media, the Intangible Cultural Heritage Visual Storytelling dataset functions as a structured digital library. It compiles multimodal cultural data, including 3D scans, images, textual narratives, audio, and video recordings, accompanied by metadata detailing the cultural, geographical, and linguistic context of each item. By organising heritage information into semantically coherent categories, the dataset emphasises its storytelling potential. The Narrative Label linked to each entry represents the cultural theme or storyline, enabling researchers and developers to create applications that showcase the diversity and richness of heritage traditions. Figure 3 presents (a) the Distribution of Narrative Labels and (b) the Distribution by Region.

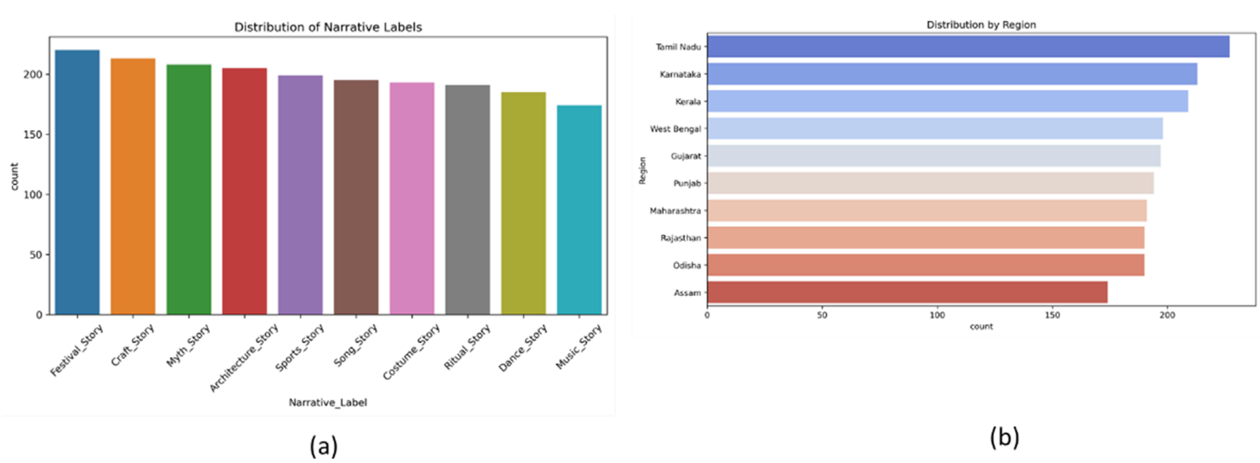

Figure 3: (a) Distribution of Narrative Labels and (b) Distribution by Region.
Source: https://www.kaggle.com/datasets/ziya07/cultural-heritage-visual-storytelling-dataset/data

3.2. Pre-Processing

Heterogeneous heritage datasets require preprocessing to ensure standardization and quality. This involves applying Gaussian filtering to images and 3D scans to enhance feature extraction, performing min–max normalization on numerical attributes, and tokenizing textual data.

3.2.1. Gaussian Filter

The Gaussian filter enhances the clarity of heritage images by reducing noise, ensuring precise feature extraction, and improving the accuracy of visual storytelling for the digital preservation of ICH. Prior to classification, the images are processed using the Gaussian filter. This method employs a Gaussian function to define a linear filter, assigning weighted values to each element. The presence of a kernel centre allows the filter to refine image details, making it particularly effective for noise reduction. This filter is well-suited for removing randomly distributed noise. Equation (1) is applied to calculate the values of each component within the final Gaussian smoothing filter:

$$g(w,z) = \frac{1}{d} f^{\frac{w^2+z^2}{2\sigma^2}} \quad (1)$$

In this context, the normalization constant is denoted by C, the Gaussian kernel's standard deviation by σ, and g(w,z) represents the output function dependent on variables w and z. The effectiveness of pre-processing in heritage data analysis is illustrated by comparing original images with Gaussian-filtered versions, demonstrating noise reduction while preserving structural details. This process enhances the accuracy of visual narrative models, contributing to the digital preservation of ICH. Figure 4 depicts heritage image pre-processing: (a) Original and (b) Gaussian-filtered images.

Figure 4: Heritage Image Pre-Processing: (a) Original vs. (b) Gaussian Filtered.

3.2.2. Min-Max Normalization

A diverse set of heterogeneous datasets, including 3D scans, images, textual narratives, and audio-visual recordings, was collected and pre-processed using min–max normalization to ensure uniformity in scale and feature comparability. The original data sample *w* can be transformed into a normalized data sample as shown in Equation (1). Typically, a feature is defined by its maximum and minimum values across the dataset. This normalization technique maps the component values of the original data sample to the [0, 1] range. Equation (1) is presented below.

$$w' = \left[\left(\frac{w - oldMin}{oldMax - oldMin}\right) * (newMax - newMin)\right] + newMin \quad (2)$$

Where *w*' represents the normalized data sample, *w* is the initial sample of data, *oldMin* represents the minimal information across every attribute of the original dataset, *oldMax* represents the maximum data across all original dataset attributes, represents the normalized dataset's minimum, and *newMax* represents its maximum.

3.2.3. Tokenisation

Textual narratives, oral transcripts, and associated metadata were tokenized into discrete units, such as words or phrases, to facilitate semantic and narrative analysis of ICH materials. Pre-processing steps, including the removal of stop words, standardization of inputs, and identification of key cultural concepts, enabled structured text analysis. This process enhances frequency analysis, pattern recognition, and the performance of the BC-LWC-RNN model, ensuring cleaner and more meaningful datasets for the generation of coherent visual narratives. Eliminating prevalent stop words is essential for improving downstream model accuracy and the relevance of narratives in heritage storytelling, as illustrated by the tokenization results. Figure 5 depicts language heritage representation.

Figure 5: Language Heritage Representation.

3.3. Bacterial Colony-Tuned Lightweight Convolutional with Recurrent Neural Networks (BC-LWC-RNN)

The sequential structure of visual storytelling is maintained by RNN, which effectively captures the progression of cultural heritage narratives. LWCNN employs additive angular margin loss and knowledge distillation to enhance efficiency, enabling compact models to perform robust feature extraction and recognition. Further optimization is achieved through BCO, which ensures faster convergence, higher accuracy, and reliable representation of heritage data. The hybrid integration of RNN, LWCNN, and BCO provides a robust framework for sentiment analysis, digital storytelling, and the preservation of ICH.

3.3.1. Recurrent Neural Networks (RNN)

RNN captures sequential heritage narratives, enabling the contextual preservation of ICH within digital libraries and supporting coherent visual storytelling. RNNs have recently demonstrated enhanced performance in tasks such as sentiment classification, image captioning, and language translation, showing significant potential in natural language processing. Data sequences provide contextual meaning in various applications; for example, a sequence of words conveys semantic information in language modelling tasks, which becomes meaningless if the sequence is disrupted. Traditional neural networks assume independence between inputs and outputs, requiring a mechanism to link current computations with prior information for full data comprehension. RNNs address this need by applying the same computation to each sequence element, with each state dependent on previous computations, effectively maintaining a "memory" of prior data. The computational flow for text processing in an RNN is as follows:

- Input is provided as a one-hot encoded vector, where w_s denotes the current input at time step s. For instance, x1 = [1 0 0 0] represents the first word of a sentence.
- t*s* denotes the hidden state at time step s, storing the network's "memory," and is computed based on both the preceding hidden state and the current input, as described in Equation (3).

$$T_s = e(Vw_s + Xt_{s-1}) \quad (3)$$

Where *e* is a non-linear function that is element-wise, such *ReLU* or *tanh*. Usually, *s*-1 is set to all zeros when determining the first hidden state. The input and hidden state weight matrices are denoted by *X* and *V*, respectively. Time step's output is denoted by *Ps*. The *softmax* function, for example, may be used to determine the likelihood of predicting the following Equation (4) in a phrase.

$$P_s = softmaxUt_s \quad (4)$$

This approach enhances the accessibility and preservation of ICH by enabling contextual interpretation of heritage data. The architecture for temporal sequence processing is illustrated in Figure 6.

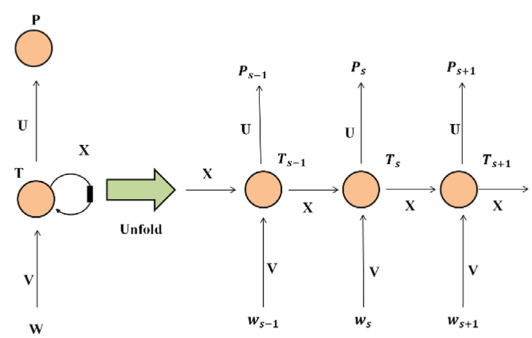

Figure 6: Temporal Sequence Processing Architecture.

3.3.2. Lightweight Convolutional Neural Networks (LWCNN)

LWCNN is employed to enhance the generation of cultural heritage narratives, integrating knowledge distillation with a specially designed additive angular margin loss function. Large networks, while computationally demanding, provide superior feature extraction capabilities. In this learning paradigm, knowledge is effectively distilled from the recurrent network to support sequential narrative generation. The resulting output serves as a semantic guide, linking spatial features from heritage scans with elements of the story sequence. While HBIM ensures structural fidelity and immersive visualization, simultaneous visual and temporal supervision enables the model to capture subtle variations in ICH, including gestures in performances, craft patterns, and rhythm or intonation in oral traditions, thereby improving narrative coherence and cultural interpretation. The BC-LWC-RNN remains lightweight and compatible with HBIM–VR integration, achieving enhanced feature extraction and narrative consistency as described in Equation (5).

$$K_1 = -\frac{1}{M}\sum_{j=1}^{M} log \frac{f^{X_{z_j}^S w_j + a_{z_j}}}{\sum_{i=1}^{m} f^{X_i^S w_j + a_i}} \quad (5)$$

In this case, $X_w + a$ comes from the completely linked layer, K_1 is the loss function's value, M is the quantity of samples, and X_z^S represents weights, a_{Zj} for bias, m for classes, w_j for the j-th sample's feature vector, and a_i for its label. S is an input feature vector. With the bias term set to zero for simplicity, Equation (6) expresses the cosine form representing the inner product between the weights and the input features:

$$X_i^S w_j = ||X_i|| w_j|| cos\theta_i \quad (6)$$

Where θ_i is the angle formed by the class weight and feature vector, and X_i is the magnitude of the feature. Weights and features are both L2-normalized, and control outputs are scaled. An additive angular margin is incorporated to enhance the distinction between cultural heritage classes. This enables BC-LWC-RNN to identify unique features and generate coherent storytelling sequences, as represented in Equation (7).

$$K_{hard} = -\frac{1}{M}\sum_{j=1}^{M} log \frac{f^{t\left(\cos\left(\theta_{z_j}+n\right)\right)}}{f^{t\left(\cos\left(\theta_{z_j}+n\right)\right)} + \sum_{i=1, i\neq z_j}^{m} f^{t\cos\theta_i}} \quad (7)$$

Where n is the angle margin, or penalty, t is the scalability factor, m is the quantity of classes, M is the batch size, Z_j is the j-th sample's label, and θ_i is the angle between features and weights. Soft targets are trained using an objective function that includes an additive angular margin. To generate feature embeddings, the RNN first processes the images. These embeddings are then passed to a fully connected layer that learns the weight parameters. L2 normalization is applied to both weights and features, converting their inner product into a cosine representation. An angular margin and scaling factor are also incorporated. For soft targets, the loss is computed using the network logits. Class-specific logits are generated after the cosine-form fully connected layer processes the features from the RNN. An angular margin is subsequently applied to the logits corresponding to the ground truth to discriminatively align the output with the labels. Differences in the logits are quantified using mean square error (MSE). Equation (8) defines the loss function for soft targets.

$$K_{soft} = \begin{matrix} \frac{1}{M}\sum_{j=1}^{M}\left(tcos\left(\theta_{z_j}^s + n\right) - tcs\theta_i^t\right)^2, i = z_j \\ \frac{1}{M}\sum_{j=1}^{M}\left(tcos\theta_{z_j}^s - tcs\theta_i^t\right)^2, i \neq z_j \end{matrix}, i \in [1, m] \quad (8)$$

Where θ_i^S and θ_i^t show the angles between the fully connected layer's weights and the attributes that were taken from the recurrent networks, respectively. The interpretation of the remaining variables remains consistent with the hard-target loss. The overall loss is computed as a weighted sum of the hard-target and soft-target losses, guiding the model to accurately classify heritage categories while emulating feature representations. Equation (9) represents the final loss function:

$$K = \alpha K_{hard} + (1-\alpha) K_{soft} \quad (9)$$

The hyper-parameter α allows adjustment of the ratio between soft- and hard-target objective functions. Multimodal heritage data integrates images or 3D scans processed through LWCNN to extract spatial embeddings, along with sequential data. These embeddings are combined with a heritage storytelling classifier, enforcing semantic connections and angular margin constraints within the discriminative semantic model. The framework employs a dual-loss mechanism: one comparing the generated narrative with semantic soft targets derived from heritage data relationships, and another evaluating the hard labels of cultural categories. These losses are weighted to update the parameters of the BC-LWC-RNN, ensuring coherent narrative generation. The optimized lightweight model reduces computational demands while maintaining performance within heritage environments.

3.3.3. Bacterial Colony Optimisation (BCO)

Model efficiency is enhanced through BCO, which ensures faster convergence, higher accuracy, and reliable visual storytelling of heritage content in digital libraries. By optimizing deep learning models with BCO, visual narratives for the preservation of ICH are generated with improved precision, efficiency, and convergence. BCO comprises five sequential stages, beginning with chemotaxis and concluding with migration. The chemotaxis and communication phase operates throughout the process, enabling bacteria to optimize their swimming and tumbling behaviours based on population data. Chemotaxis and communication jointly monitor the bacterial environment. There are two forms of bacterial chemotaxis: swimming and tumbling, where the swimming direction is determined randomly during tumbling. The optimal search direction and turbulence direction interact to update the search vector and bacterial positions, as described in Equation (10).

$$Position_j(S) = Position_j(S-1) + D(j) * \left[e_j.\left(H_{best} - Position_j(S-1)\right) + \left(1-e_j\right) * \left(O_{best_j} - Position_j(S-1)\right) + turb_j\right] \quad (10)$$

Where the most recent location of the th solution, is a scaling, is a weight, is a turbulence. Equations (11) and (12) can be interpreted as follows: during bacterial swimming, there is no turbulence direction guiding the movement toward an optimal state.

$$Position_j(S) = Position_j(S-1) + D(j) * \left[e_j.\left(H_{best} - Position_j(S-1)\right) + \left(1-e_j\right) * \left(O_{best_j} - Position_j(S-1)\right)\right] \quad (11)$$

$$D(j) = D_{min} + \left(\frac{Iter_{max} - Iter_i}{Iter_{max}}\right)^m \left(D_{max} - D_{min}\right) \quad (12)$$

Where, $turb_j$ is the turbulent direction. e_j is in the range $\in \{0,1\}$ The chemotaxis step size is $D(j)$. H_{best} is the global best, and O_{best} is the personal best. m is the chemotaxis step's size. The present iteration is called $Iter_i$, while the maximum number of iterations is called $Iter_{max}$. During the elimination and reproduction phase, high-energy bacteria replicate to generate new individuals, whereas low-energy or infected bacteria are removed. High bacterial energy signifies a strong capacity for resource acquisition. In the migration phase, bacteria move within a defined search space if certain conditions are met, naturally exploring for the latest resources based on specific probabilities. The search begins with a randomly selected artificial bacterial population, where each bacterium represents a potential solution to the optimization problem. Bacteria communicate their fitness or solution quality with one another. After multiple chemotaxis cycles, bacteria with higher fitness and superior solutions are more likely to reproduce, while ineffective bacteria are eliminated or their influence on the search process is reduced. Mutation occurs when a small proportion of the bacterial population randomly changes traits or positions. Within digital libraries, the hybrid RNN–LWCNN–BCO framework improves the accuracy, efficiency, and effective preservation of ICH.

4. Result

The BC-LWC-RNN model applied tokenization, normalization, and feature extraction to effectively process diverse heritage datasets using Python. The results demonstrated seamless integration with HBIM and VR environments, enabling interactive storytelling of ICH and achieving high accuracy in generating coherent visual narratives. The network graph depicts extensive semantic relationships across cultures by linking narrative labels to ICH categories. This hierarchical mapping ensures consistent cultural narratives while broadening the scope of automated visual storytelling. It also enhances interpretability, user engagement, and preservation within digital libraries. Figure 7 illustrates the network graph of ICH types and narrative storytelling labels.

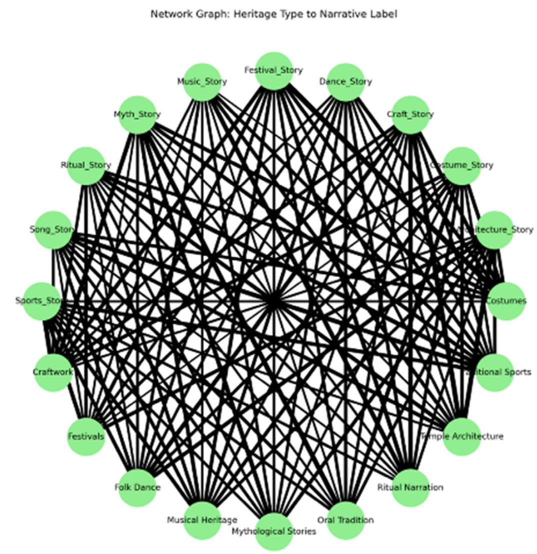

Figure 7: Network Graph of Intangible Cultural Heritage Types and Narrative Storytelling Labels.

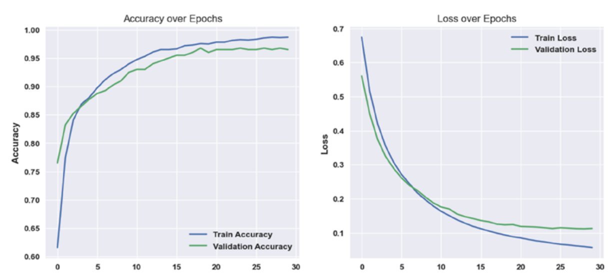

Figure 8: Performance of Model Training: Accuracy and Loss across Epochs.

Stable convergence is demonstrated by the graph, which displays the BC-LWC-RNN model's training and validation accuracy (62%–98%) and loss reduction (0.68–0.08) over 30 epochs. This confirms that visual storytelling for ICH is accurate, efficient, and reliable. Figure 8 presents the model training performance, showing accuracy and loss across epochs. Moreover, the stacked bar chart illustrates the distribution of heritage types across 11 languages, with counts ranging from 120 to 220 per category. This representation promotes the preservation and accessibility of ICH within digital libraries across multiple languages. Figure 9 depicts the multilingual distribution of heritage types.

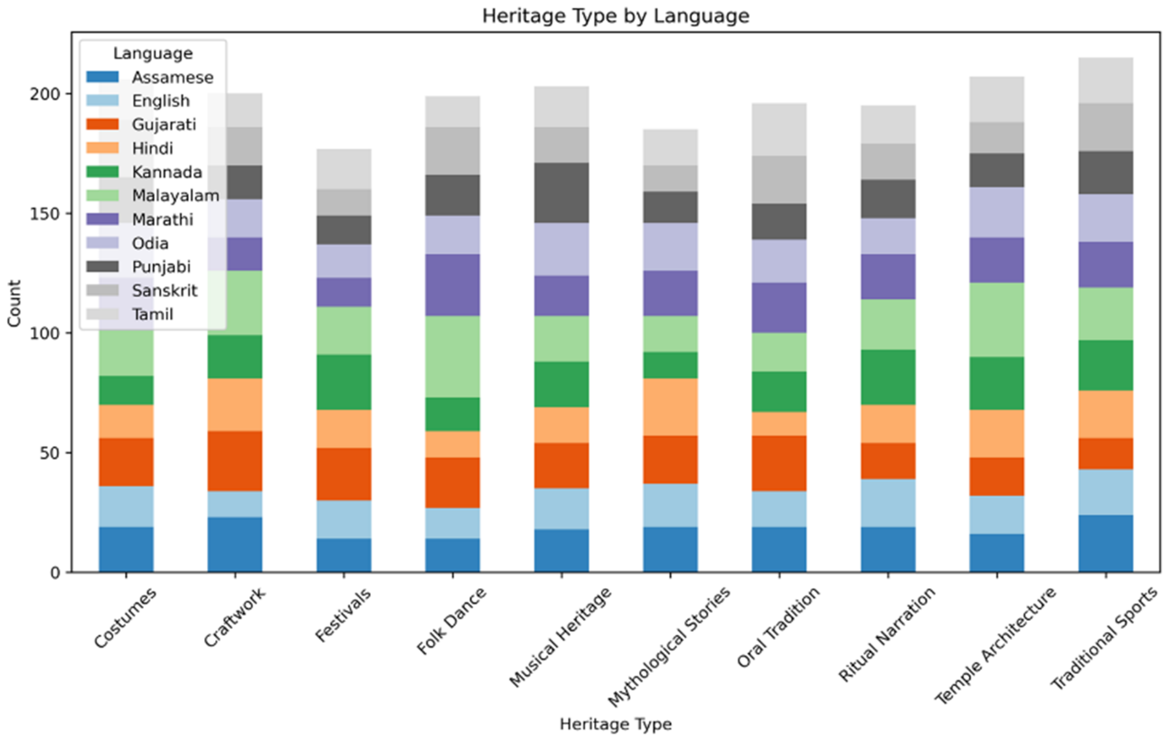

Figure 9: Multilingual Distribution of Heritage Types.

4.1. Performance Analysis

The Customized 3D Convolutional Neural Network (3D CNN) Zhao (2024) noted that this technique has a limitation, as it depends on large, high-quality ICH image datasets, which may be difficult to obtain. This limitation can lead to biases and reduced generalizability across diverse cultural systems. By integrating multiple heritage datasets, the BC-LWC-RNN model addresses the data scarcity and bias issues associated with 3D CNNs, ensuring scalable, generalizable, and high-performance visual storytelling across various ICH systems.

Accuracy: Accuracy measures the proportion of correct predictions among all predictions made. The BC-LWC-RNN model achieved an accuracy of 98.03%, outperforming the 3D CNN in correctly classifying heritage data.

Precision: Precision indicates the proportion of true positive predictions among all positive predictions, reflecting the reliability of positive forecasts. The BC-LWC-RNN model achieved a precision of 97.73%, demonstrating high reliability in predicting positive cases.

Recall: Recall represents the proportion of true positive instances correctly identified by the model, reflecting its ability to detect all relevant cases. With a recall of 98.23%, the BC-LWC-RNN model effectively identifies nearly all relevant positive examples in the dataset.

F1-score: The F1-score, the harmonic mean of precision and recall, indicates the model's overall capability to detect positive instances. The BC-LWC-RNN model achieved an F1-score of 97.85%, indicating a strong balance between precision and recall.

Multi-Method Machine Learning Performance Metrics are presented in Table 1 and Figure 10. This approach ensures the preservation of cultural context, integrates diverse datasets, addresses biases and data limitations, supports scalable and flexible HBIM workflows, and generates high-performance, structured visual narratives that enhance the accessibility and understanding of ICH.

Table 1: Multi-Method Machine Learning Performance Metrics.

Models	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
3D CNN	97.88	97.12	97.55	96.99
BC-LWC-RNN	**98.03**	**97.73**	**98.23**	**97.85**

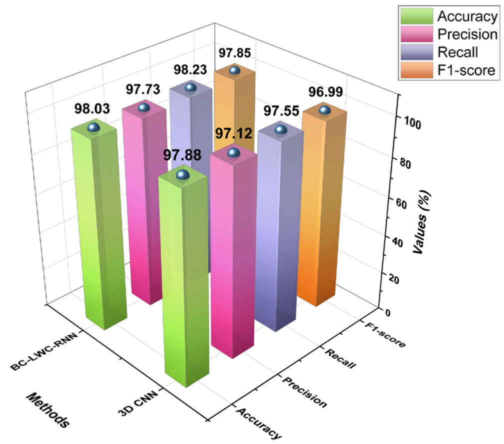

Figure 10: Multi-Method Machine Learning Performance Metrics.

5. Conclusion

The integration of BC-LWC-RNN with HBIM and immersive visualization enables advanced preservation and dissemination of ICH. This framework enhances interpretative storytelling within digital libraries, strengthens semantic connections, and generates coherent visual narratives by processing diverse heritage resources. The outcomes demonstrate deeper cultural understanding and support sustainable conservation through improved accuracy, efficiency, and user engagement. The method provides innovative design strategies for the long-term digital preservation of cultural knowledge and practices, ensures the continuity of intangible traditions, and promotes global accessibility. The BC-LWC-RNN model achieved 98.03% accuracy, 97.73% precision, 98.23% recall, and 97.85% F1-score in identifying elements of ICH.

5.1. Limitations and Future Scope

A primary limitation is the dependence on high-quality, diverse datasets; insufficient or biased cultural data can reduce narrative coherence, lower accuracy, and limit the inclusivity of ICH representation. Future developments may involve multimodal data fusion, real-time VR/AR storytelling, and adaptive AI customisation, enabling inclusive, immersive, and globally accessible platforms for the preservation and engagement with intangible cultural assets.

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