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From Physical to Virtual: Enhancing the Representation of Intangible Cultural Heritage Using Mixed Reality

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Abstract

Intangible Cultural Heritage (ICH), including oral traditions, performing arts, and rituals, is at risk of fading due to modernization and limited preservation methods. Existing digital preservation methods often lack multi-modal integration and fail to provide a fully immersive representation of ICH. The aim is to develop an advanced framework that integrates Mixed Reality (MR) and Deep Learning (DL) techniques to create an immersive and accurate digital representation of ICH. The objective is to enhance the accessibility and longevity of cultural heritage by leveraging multi-modal data sources, including audio, textual, and visual data. First, pre-processing techniques such as noise reduction, tokenization, and data augmentation are applied to improve data quality. Next, feature extraction is performed by using Convolutional Neural Networks (CNN) for audio and visual data and Word2Vec for textual data, ensuring an accurate understanding of cultural expressions. These extracted features are then fused at the feature level, integrating multiple data modalities for a coherent and enriched representation of ICH. The processed data is integrated into a Mixed Reality environment using platforms like Unity and Unreal Engine, allowing real-time interaction through gesture recognition and voice-based controls. A Backpropagation Neural Network (BPNN) is employed to optimize content generation, ensuring adaptive and high-fidelity digital reconstruction. The proposed method is implemented by using Python 3.10.1. The proposed approach is evaluated based on realism, cultural authenticity, system performance, and knowledge retention rate, demonstrating MR-driven ML models that significantly enhance the accessibility, preservation, and educational impact of ICH.

Keywords: *Mixed Reality (MR), Deep Learning (DL), Multi-Modal, Backpropagation Neural Network (BPNN), Intangible Cultural Heritage (ICH).*

Introduction

Cultural heritage includes both tangible and intangible forms of traditions, oral hits, arts, rituals, and craftsmanship transmitted from one generation to the other (Hulusic et al., 2023). Physical conservation of tangible cultural heritage artifacts, and historical sites allows for the preservation of heritage, but the intangible cultural heritage (ICH) poses different types of challenges (Liu, 2023). ICH exists in human expression and interaction for preserving and transmitting the complexity of the physical system. Digital technology has been rapidly developed by Mixed Reality (MR). VR applications enable cultural heritage accessibility to individuals through digital enhancing features and interactive historical reconstructions (Zheng, 2024). MR in the virtual world constitutes an immersive and engaging experience that falls under augmented reality (AR) and virtual reality (VR). This technology has become a powerful tool that allows cultural history to preserve innovative ways of recording, clarifying, and sharing cultural history (Mantzou et al., 2023). MR applications help to view historical stories by experiencing interactive narratives of traditional arts in digital versions and attending virtual festivals. The

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technological interventions preserve cultural traditions by maintaining their authenticity to ensure the survival of cultural traditions in the digital age worldwide (Nisticò, 2024). MR provides experiential learning opportunities to interact with the cultural elements. Various factors include globalization, urbanization and the disappearance of traditional knowledge to transmit the systems of ICH (Zhang, 2023). MR could improve the visibility and engagement of ICH for the purpose of an inclusive, interlinked and culture-sensitive society. MR could serve as an important platform for the younger generations to interact and vocalize their heritage with new innovative ideas, sustaining and maintaining traditional knowledge and practices for individuals (Wu, 2022).

MR played an important role in cultural preservation through the application of ICH representation. MR technologies help to widespread the use of cultural institutions, communities and individuals to preserve and disseminate the intangible heritage (Liu et al., 2022). MR facilitates to access cultural customs and traditions around the world so that the culture identifies all different cultures (Trunfio, 2022). MR platform allows users from different geographic regions to explore the cultural heritage to improve their lifestyles. Additionally, MR was a tool of cultural revitalization, especially for communities threatened with different extinctions. The development of MR-based cultural heritage experiences often requires significant technical knowledge to access the communities and institutions when engaging with ICH. The expenses of model and digital-related issues might prevent the widespread use of MR technology in ICH preservation (Shim et al., 2024). Due to the potential of MR in cultural heritage preservation, there were still some challenges that must be handled. The aim is to develop MR applications that accurately represent the ICH, and the collaborative approaches integrate cultural practitioners and historians (Sun et al., 2024). Cultural practices were digitized, thus leading to a cultural appropriation and misinterpretation concern, emphasizing the necessity of community participation in the design and embedding of MR experiences (Schauer & Sieck, 2023). MR was an expensive way to develop and maintain MR applications in cultural heritage (Manchanda et al., 2015).

The aim is to develop an advanced framework that integrates MR and DL techniques to provide an accurate and engaging digital interpretation of ICH. An innovative novel of the Backpropagation Neural Network (BPNN) algorithm was used to optimize the creation of material, guaranteeing high-fidelity and adaptable digital reconstruction.

Key Contributions

- The audio, text, and image datasets of cultural heritage were collected from Kaggle. Pre-processing methods were used to enhance the quality of the data, including data augmentation, tokenization and noise reduction.
- Feature extraction used Convolutional Neural Networks (CNN) for audio and visual data and Word2Vec for textual data to ensure an accurate understanding of cultural expressions. MR environment enables real-time interaction through voice-based controllers and gesture detection.
- The backpropagation neural network (BPNN) algorithm was used to enhance high-tech remodeling and content creation. The simulation results evaluate the realism, cultural authenticity, system performance and knowledge retention rate.

The research is comprised of the following sections: In Part II, the relevant literature is presented along with a summary; in Part III, the strategy and methodology are detailed; in Part IV, the experimental and assessment results are presented; in Part V illustrates the discussion of the research findings; and in Part VI, the investigation is concluded.

Literature Review

The virtual heritage (VH) domain identified contextual relationships, engagement, and cooperation as essential components of interaction design that impact user' experiences and cultural learning in VH applications (Bekele et al., 2021). The result findings demonstrated the cultural learning of VH. A community's live traditions and customs design pattern was known as ICH (Galani & Vosinakis, 2024). The ICH model was digitized and disseminated by using a variety of instruments. Mobile AR was an effective tool that constituted a seamless merge of digital and physical information. The outcome demonstrated how the physical size model affects the experience. Preserving cultural heritage was a multifaceted process that incorporated various techniques, such as 3D modeling, AR, and VR systems (Dimara et al., 2024). The development of MR techniques used for preserving cultural assets. The experimental outcome demonstrated how digital cultural sites prevent additional degradation.

Human augmentation was made possible by the metaverse, which drove extended reality (XR) technology that improves intellectual, sensory, and physical skills (Innocente et al., 2024). A metaverse service stimulated interactions between multiple users in a realistic VR experience while protecting intangible assets of culture. The outcome demonstrated the enhanced integration of cultural heritage surroundings and favourable user experiences. The projection modeling constituted MR technology that includes spatial augmented reality (SAR) for many cultural applications (Nikolakopoulou et al., 2022). The architectural heritage serves to promote culture and increase public knowledge of historic structures or landscapes. The experimental outcome demonstrated the historical occurrences and seasonal farming operations of the 3D model. MR system was developed to provide a realistic and engaging experience for exploring cultural heritage locations (Ashraf et al., 2024). The system's effectiveness and user involvement were evaluated by using a user assessment, revealing customer preferences and possibilities of MR technologies to preserve and promote cultural heritage. The findings demonstrated how the application affects multiple interactions, connectivity, and participation.

VR training tools were created that allow artificial environments by virtual setting (Paulauskas et al., 2023). Combining virtual and real-world settings, MR enabled users to engage in both digital and real-world things simultaneously. According to the findings of sociological research, 75% of participants had a favourable opinion of VR usage. ICH assets include conservation, marketing, and cultivation of talent for VR simulation. These elements were essential for the sustainable growth of cultural heritage (Yang et al., 2024). The platform required 3D modeling technology and VR cinematography. The outcome demonstrated the model's digital copy recovery and conventional video records. To maintain ICH, the VR technology utilized paper-cutting artwork. The integration of contemporary technology components, VR effectively digitized and extensively distributed artwork (Zhao & Kim, 2024). The VR system incorporated modern technologies like modular layout and three-dimensional modeling. The experimental outcome demonstrated the cultural experience of users.

The design and production of dynamic graphical systems display 3D segments of both virtual and real things by combining computer-generated holograms (CGH) and digital holograms (DH) (Tang & Zhang, 2023). The production of extensive graphic databases was made possible by ICH. The outcome demonstrated the spatial flash modulator's dispersion of real and virtual information. The use of MR has become essential in promoting cultural heritage. Through the use of virtual portals, objects were inaccessible in the original form that could be virtually visited and integrated into the actual world (De Luca et al., 2023). MR application blends physical reality with the help of virtual restoration. The outcome demonstrated the excessive amount of user interest. ICH was an essential component for collective human inheritance. With the help of realistic animated images and spatial 3D audio, the specific ambiance and virtual version of the system were accurately captured (Khalloufi et al., 2023). The experimental outcome demonstrated how VR technology integrated consumers into cultural heritage activities.

The digitalization of cultural material has aided some technologies like three-dimensional printing (Anastasovitis et al., 2024) Virtual cultural legacy was anticipated significantly by the Internet of Things (IoT) systems. The experimental outcome demonstrated how virtual worlds have been used by actual cultural heritage associations. AR tool used for promoting the cultural heritage termed Innovative Cultural Experience (ICE) (Kazanidis et al., 2022). The ICE incorporated innovative technology like visible screens, AR, motion detectors, and multimedia content to create a distinctive personal vision of mass-touring environment. According to the findings, ICE was a comprehensive system that could offer an AR experience. The focus of exhibiting intangible cultural assets has shifted from conventional static displays to dynamic conditions that highlight the essence of cultural property (Yu et al., 2024). The cultural kinetic displayed urgently need a complete full-chain makeover for cultural improvement. The outcome demonstrated the cultural imports and principles of cultural heritage.

AI technology was used to improve the digital inheritance and advancement of ICH (Dai et al., 2024). The digitalization of intangible cultural material constituted by IoT systems posed difficulties for its transmission and maintenance. The outcome demonstrated the trends and precise replication of cultural components, especially in the creation of intricate designs. The preservation of cultural identity and cultural heritage constituted the growth of local cultural assets (Yan & Li, 2023). The government must adopt ICH in education after defining its own roles and responsibilities in maintaining cultural heritage. The outcome demonstrated how self-management recipients safeguard ICH in a sustainable manner.

Problem Statement

In the digital era, the preservation and propagation of ICH was a difficult task that helped to visualize and transmit the generation. The traditional methods of cultural preservation often fail to verify the immersive experiential dimension associated with the practice, ritual, and oral traditions. The integration of MR in cultural heritage preservation faces obstacles such as technological constraints, accessibility issues and validity of digital story. The MR of ICH offers a transformative approach by bridging the gap between physical and virtual worlds, when interactive and immersive representations of ICH were founded. It helps to explore ICH-themed MR applications that improve cultural representation, transmission, and engagement. The suggested approach helps to progress the work of digital heritage activities, cultural conservation on sustainability, and cultural education experiences.

Methodology

The reliability of cultural heritage includes audio, text, and image data collected from Kaggle. To improve data quality, the preprocessing techniques include noise reduction, tokenization, and data augmentation. Accurate comprehension of cultural expressions was ensured by feature extraction utilizing Convolutional Neural Networks (CNN) for audio and visual data and Word2Vec for textual data. MR environment enables real-time interaction through voice-based controllers and gesture detection. A Backpropagation Neural Network (BPNN) was utilized to improve content production and high digital renovation. Figure 1 represents the overall flow of the ICH using MR.

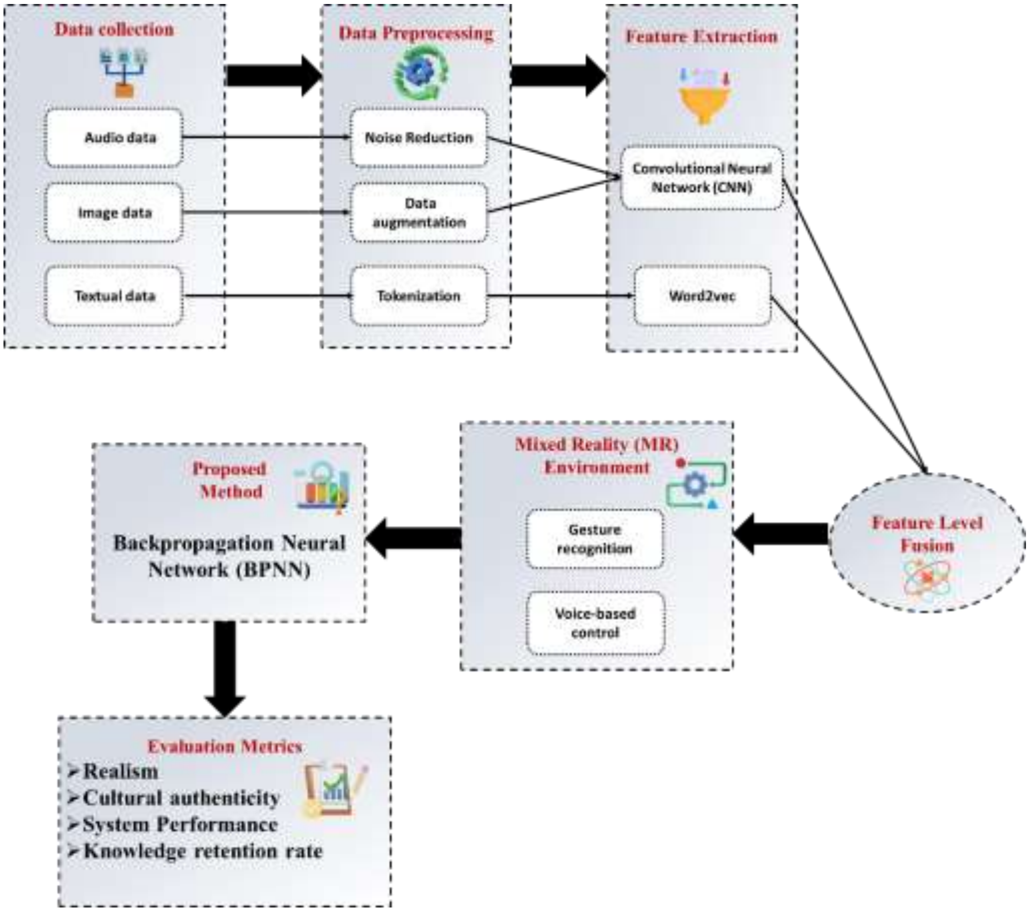

Figure 1: Overall flow of the ICH using MR

Dataset

Here, three datasets of audio, textual, and image data were used to enhance the accessibility and longevity of cultural heritage.

Audio Dataset

An audio dataset was collected from Kaggle. It includes more than 170,000 musical compositions from various genres and civilizations. Exploration of music beyond acoustic qualities was made possible by the descriptive annotations for each recording, which offer emotional and contextual insights. To train models for tasks like music categorization, creation, and sentiment analysis, the dataset contains lyrics, musical instruments, and sound descriptions. The collection of AI-driven music analysis provides annotations for musical components like melody, rhythm, and harmony.

Source: https://www.kaggle.com/datasets/googleai/musiccaps

Text Dataset

A text dataset was collected from Kaggle. Data from the intangible cultural treasures was included that showcase a wide range of customs, behaviours, and abilities acknowledged as essential components of cultural identity. This dataset includes information about heritage cultures such as specification, region of origin, and year of placement. It helps to preserve the information about intangible cultural assets while fostering a comprehension of cultural diversity.

Source: https://www.kaggle.com/datasets/joebeachcapital/unesco-dive-into-intangible-cultural-heritage

Image Dataset

An image dataset was collected from Kaggle. The architectural history elements constitute the collection of images used to create deep learning (DL) algorithms and specialized methods for classifying the visuals of architectural history. It includes 64x64 pixel images that were divided into many heritage-related classifications, which makes it appropriate for tasks like cultural asset preservation and image categorization. The automatic identification of heritage sites displays a wide variety of architectural elements, such as statues, facades, and decorative details.

Source: https://www.kaggle.com/datasets/ikobzev/architectural-heritage-elements-image64-dataset?select=train

Data Preprocessing

Data processing is used to preprocess the raw data. Unprocessed data was transformed into a readable format by data pre-processing, a necessary step in data exploration. Data preprocessing includes noise reduction, tokenization, and data augmentation.

Noise reduction techniques used for preprocessing data becomes essential for both improving the performance and accuracy of MR applications to protect ICH. The precision of user engagement and learning heavily relies on accurate data processing within cultural assets applications utilizing MR technology. Noise reduction techniques involve a Gaussian filter. The Gaussian filter was one of the most important functions to preprocess the audio data. The most widely used technique for filtering is termed as Gaussian filtering, which uses weights expressed in equation (1).

$$\overline{w}_{ji}\alpha \exp\,(||x_j - x_i||\,), j = i(1)$$

The geographical filtering method is known as Gaussian filtering. A common technique is used for denoising in the Gaussian filter, which tends to produce smooth noise and clearly reduces data, particularly exterior clarity. Although it allows noise to stay reasonably steady, Gaussian smoothing, sometimes referred as lower-pass filtering, preserves the noises to lower-frequency components by lowering high-frequency characteristics like distortion and borders.

Tokenization was a preprocessing step used to digitize and analyze the produced textual and multimedia content of ICH. It helps to increase cultural education and make indigenous knowledge and intangible traditions relevant in the digital era by tokenization, which helps to build language models that support real-time translations, making ICH experiences more inclusive. Using the natural language processing (NLP) approach of tokenization, a collection of texts was distinguished into meaningful words, clauses, signs, statements, and other parts. Through the conversion of unstructured material into a structured format, tokenization streamlines text analysis and facilitates the use of NLP techniques. Tokenization allows for improved comprehension and processing by maintaining the semantic linkages and context of words in sentences. Tokenization was necessary to convert unprocessed text into format.

The **data augmentation** leads to enriched digital models of ICH for traditions rituals and folklore authenticity for better model generalization. It could handle existing ICH digitization data to provide better identification methods for cultural expressions. Data augmentation helps to prevent fitting issues during the training phase by improving the data and adding a small amount of error images. It helps to ensure that every category has a similar quantity of images. Two augmentation techniques, flipping and rotating, were applied to the training images to increase their potency and efficiency. Images that were vertically orientated were flipped by flipping them up and down and right and left.

Feature Extraction

The feature extraction used in machine learning and data analysis minimizes the dimensionality of data. It cracks unprocessed data into a collection of useful characteristics that make analysis easier while preserving details. Here, the feature extraction includes CNN and Word2Vec.

CNN helps with the precise identification and digitization of elaborate patterns together with textured elements and cultural heritage found in historical artifacts and traditional performance crafts. The extracted features boost MR realism. So, users could experience cultural heritage through VR or AR environments. The CNN enters the image and audio directly as data, supporting the idea of pixel-by-sparse representation. A few particular pattern categorization issues constitute at a specific time. Audio and images are all the inputs for the multichannel learning model. CNN was employed for saliency detection and restriction was avoided by super pixel, then the segregated network was known as pixel inputting. After processing across all channels, the data was transformed into segmented pixels by using cross-correlation and down-sampling. The activation function determines the output value of the image that passes through the input layer from the convolution layer were expressed in equation (2).

$$w^m = g(X^m w^m + c^m) \quad (2)$$

Where, the activation function indicated as g, offset by c, weight by ω, and the number of layers by m. A learnable kernel convolution of several feature maps from the preceding layer during the forward propagation phase produces a fresh feature map by the function of activation expressed in equation (3).

$$w_i^m = g\left(\sum_{j \in N_i} W_j^{m-1} * l_{ji}^m + c_i^m\right) \quad (3)$$

The current layer's initial feature map indicated as $m-1$. As the i convolution kernel, represented by W_i^m, the offset value c_i^k represents the initial mappings for the current layer and the i preceding layer. The convolutional layer is followed by the down-sampling layer, which ignores the target's pitch and rotation that affect the relative location. Equation (4) is used to determine the down-sampling layer.

$$w_i^m = g\left(\beta_i^k down\left(w_i^{m-1}\right) + c_i^k\right) \quad (4)$$

The kernel was updated by using gradients obtained from convolution and pooling processes. In multi-classification issues involving categories and sample counts, the squared difference loss function was expressed in equation (5).

$$F^N = \frac{1}{2}\sum_{m=1}^{N}\sum_{l=1}^{d}\left(s_l^N - z_l^N\right)^2 (5)$$

Here, F^N represents the total error and ct_l^N depicts the dimensional label of the model. The cross-correlation followed by the layer of pooling that retrieved image and audio characteristics and correlation features was utilized for classification. The primary function intends to decrease the feature dimension. The reduction of visual features enhanced the pooling layer and transmission layer that extract the fully connected layer of CNN.

The NLP technique of Word2Vec serves as a popular feature extraction method that boosts the preservation and interaction processes of ICH in MR environments. The conversion of cultural element text descriptions through Word2Vec vectorization processes allows the development of rich contextual MR experiences. Through this method, users could easily explore the linguistic components like historical and artistic aspects of ICH because it brings together conventional storytelling methods with present-day digital engagement. An independent toolkit known as Word2vec was used to create word vectors. Word2vectors have the following properties, such as the vector proximity between the Word vectors that might be used to quantify the connection between words. The gap between two-word vectors was smaller and it might be semantically relevant to the words. Word2vec was often used for NLP applications such as text categorization, sentiment assessment, identical terms, and segmentation.

Feature-Level Fusion

Feature-Level Fusion was a sophisticated data integration method that combines many modalities, including text, images, and audio, at the feature extraction stage to improve the analysis and interpretation. This method allows cultural customs, practices, and artistic expressions to be preserved, made accessible, and interactively visualized on ICH. The extracted features of audio, text, and image constitute the feature level for integration. Higher contextual precision of ICH becomes possible through the combination of extracted features. The process of combining feature vectors from training data with the weighted network module, using numerical data, is known as feature fusion. It allows the suggested model to use as many features as feasible for subsequent classification. By enabling collaboration among various cultural components, fusion enhances cross-model learning. Where, $W_s = (w_{s1}, w_{s2}, \dots, w_{tn}) \in Q^m$ are the extracted features, Q^m represents the m-dimensional array. W_f and W_s were combined to obtain the feature fusion, and the outcome indicated as $(n+m)$ dimensional array. Equation (6) was used to realize the feature fusion.

$$W_e = W_s \oplus W_f = (w_{s1}, w_{s2}, \dots, w_{sm}, w_{f1}, w_{f2}, \dots, w_{fn}), W_e \in Q^{m+n} \quad (6)$$

The fused feature vector W_e represents the new vector $(w_{s1}, w_{s2}, \dots, w_{sm}, w_{f1}, w_{f2}, \dots, w_{fn})$ that was constructed from the components $(w_{s1}, w_{s2}, \dots, w_{sm})$ of W_s and $(w_{f1}, w_{f2}, \dots, w_{fn})$ of W_f.

Mixed Reality (MR) Environment

MR environments deliver an interactive setting that merges physical reality with digital elements to let their elements interact simultaneously in real-time. It constitutes powerful engines such as Unity and Unreal Engine that allow users to implement advanced MR capabilities through high-quality digital renderings, physics calculations, and active data information processing. The MR technology makes it possible to develop applications throughout education, cultural preservation, health care and entertainment domains. Real-time interaction was a main factor in MR environments through gesture recognition and speech input systems. Users could complete gesture recognition operations that follow hand motions to handle digital objects or resize the elements with natural movements. The incorporation of voice commands allows users to interface with the system through speech commands for navigation and function activation. Various interactive features enhance accessibility together with immersion, which makes MR applications both convenient to use and adaptable to multiple circumstances. Spatial computing enables users to navigate VR of historical urban centres and watch historic occasions of digital items. Heritage preservation receives enhanced benefits through accessibility growth, which enables later generations to experience it. The combination of 3D modeling with immersive storytelling enables MR techniques to construct cultural experiences that recreate historical environments and traditional elements. MR provides a new method to interact with digital content which combines speech input, gesture recognition and high-fidelity 3D models. It was an essential tool for educational purposes, training purposes, entertainment purposes and cultural heritage preservation.

Backpropagation Neural Network (BPNN)

BPNN was a machine learning algorithm used to analyze and classify ICH aspects through data pattern learning for traditional practices, rituals, and performances. It helps to create modern techniques for preserving and displaying ICH by using contemporary presentation methods. The application of BPNN technology facilitates exploration and pattern prediction for traditional cultural artifacts, including crafts and arts and performances. MR delivers an enhanced interactive view to users. BPNN was a traditional supervised learning technique that combines the methods of back-propagation and feed-forward neural networks. The nonlinear adaptation and modification characteristics were utilized in several sectors for the exceptional performance of the model. The pillar stability was assessed by using the BPNN model to predict anxiety levels. The BPNN algorithm includes five stages, such as initialization of biases and weights, data propagated into feedforward, errors were back-propagated, optimization of biases and weights, and termination conditions judged. The random integers were used to initialize the weights and bias at the layers of output and the layers of hidden. The quantity of input was handled by the input layer. The hidden layer creates the potential of nonlinear mapping by increasing the number of control levels and mechanisms for activation. Figure 2 represents the architecture of BPNN.

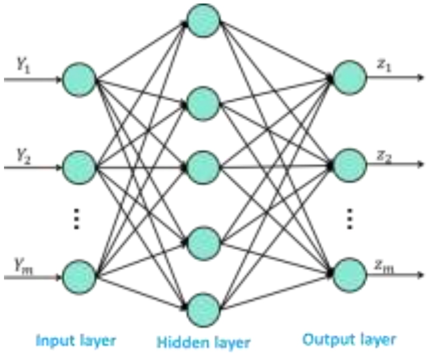

Figure 2: BPNN architecture

The output layer was responsible for generating specific data. The bias indicates the degree of difficulty in producing activation, whereas the amount of each weight indicates the degree of linked neurons to impact the output. The concealed layer and output layer were expressed in equations (7 and 8).

$$z_i = e\left(\sum_{j=1}^{m}\left(x_{ji} \times w_j\right) - \theta_i\right)(j = 1,2, \dots, m; i = 1,2, \dots, n) \tag{7}$$

$$y_l = e(\sum_{i=1}^{n}(x_{il} \times z_i) - \theta_l)(i = 1,2, \dots, n; l = 1,2, \dots, k) \tag{8}$$

The function of $e$illustrates the activation function, while $w, z, and\ y$represent the output values of layers. Additionally, $m, n, and\ k$illustrate the number of neurons. In the output layer, the error of neuron depicts as F_l and the concealed layer represent asF_i.The error depends on weights, the following are the tuning weights of ΔX_{ji}among the input and concealed layers and ΔX_{il}across the concealed and output layers were expressed in equations (9 and 10).

$$\Delta X_{ji} = -\eta \frac{\partial F_i}{\partial x_{ji}} \tag{9}$$

$$\Delta X_{il} = -\eta \frac{\partial F_l}{\partial x_{il}} \tag{10}$$

Here, η represents the rate of learning. The modified weights of $x_{ji}(s + 1)$and $x_{il}(s + 1)$were expressed in equations (11 and 12) as follows.

$$x_{ji}(s + 1) = x_{ji}(s) + \Delta x_{ji} \tag{11}$$

$$x_{il}(s + 1) = x_{il}(s) + \Delta x_{il} \tag{12}$$

The training procedure was carried out until the convergence requirements were met or not.

Experimental Results

The experiment setup was performed in the programming language of Python 3.10.1 and is used to implement the suggested method on a Windows 11 system with an Intel i7 core CPU and 8GB of RAM. It provides an in-depth explanation of the experimental outcomes.

Peak Signal-To-Noise Ratio (PSNR): The PSNR metric was frequently used to assess the quality of compression and reconstruction in image and video processing. It compares the maximum possible signal value usually referred as the pixel value with the noise introduced during processing. PSNR was expressed in decibels (dB), with higher values denoting better quality and less distortion.

Structural Similarity (SSIM): SSIM was utilized to compare the two images. Structural information, contrast, and brightness fluctuations were used to assess how similar or different images were from one another. SSIM was more sensitive and utilized perceptual quality to determine how individuals visually interpret image degradation. Figure 3 depicts the graphical representations of PSNR & SSIM.

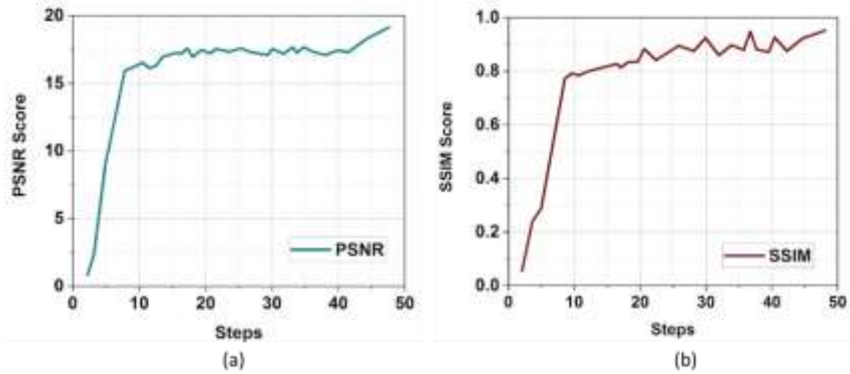

Figure 3: Output of (a) PSNR and (b) SSIM

Realism measurements evaluate how well a system simulates in real-world situations. The realism measure avoids additional computational costs to users while ensuring a realistic experience through the system. The realism measure of the suggested model BPNN has various metrics such as visual fidelity (93%), audio quality (87%), and semantic accuracy (90%). Figure 4 represents the graphical representation of realism.

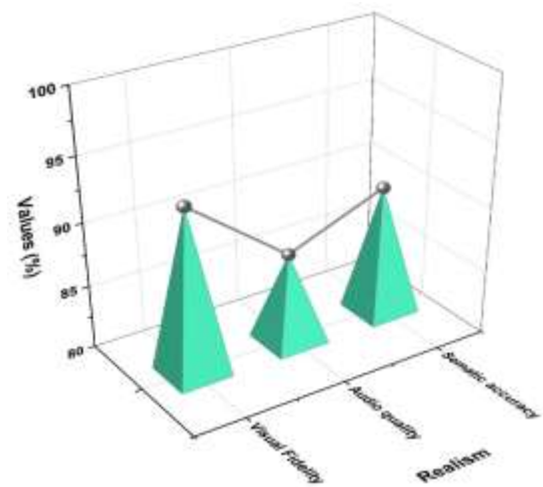

Figure 4: Graphical representation of realism

Cultural authenticity in digital system representation measures the successful capture of cultural elements to achieve respect and appreciation from the user's background. The measurement of this statistic relies on expert validation through assessments in the cultural field about how customs, symbols and stories were presented. The cultural authenticity measures of the suggested model BPNN have various metrics, such as cultural representation (94%) and cross-cultural acceptance (87%). Figure 5 depicts the cultural authenticity.

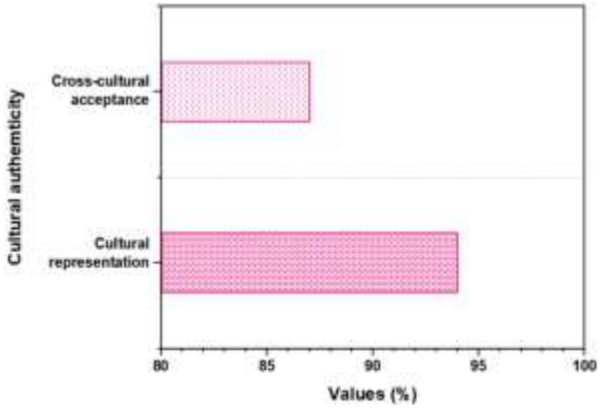

Figure 5: Graphical representation of Cultural authenticity

The system performance metrics evaluate how efficient and quick a system operates during active use. System performance quality stands as a significant element for measuring overall system effectiveness because it shapes user-level satisfaction outcomes. The system performance of the suggested model BPNN has various metrics such as latency (140 ms), frame rate (67.70 ms), and scalability (200 ms). Figure 6 illustrates the system performance.

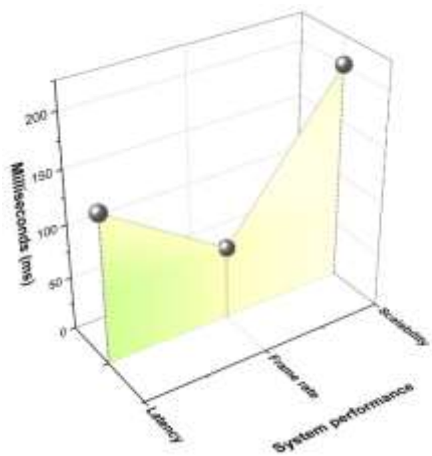

Figure 6: Graphical representation of System performance

Learning experience effectiveness could be measured through the knowledge retention rate because it determines the percentage of user information. The retention rate constitutes how well the learning outcomes persist over time. The knowledge retention rate of the suggested model BPNN has various metrics such as learning rate (80%), educational efficiency (85%), and cultural practice engagement (70%). Figure 7 represents the knowledge retention rate.

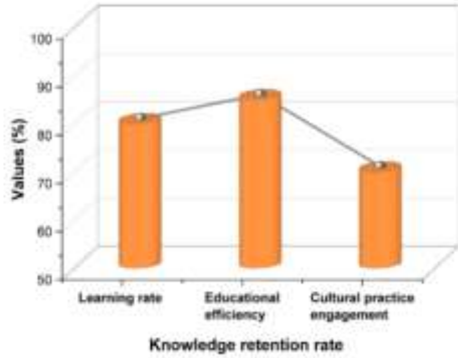

Figure 7: Graphical representation of knowledge retention rate

Discussions

MR techniques improve the visibility and engagement of ICH for the purpose of an inclusive, interlinked, and culture-sensitive society. MR platform allows users from different geographic regions to explore the cultural heritage for improving their lifestyles. The protection of intangible cultural assets with personal data becomes problematic when such assets need protection in the digital environment. The success rate of metaverse integration of cultural heritage relies on accurate content and adjustable user experiences through technical limitations between users and the expensive barriers for wide implementation. The exact level of human augmentation precision in developing enhanced mental abilities together with sensory functions and physical capabilities stays unclear because virtual environment exposure could cause users to develop cognitive and health problems. Metaverse service regulations and legal frameworks constitute difficulties in specific-region standardization for implementing different territories of VR techniques. To overcome this, the proposed method of the BPNN approach was used to improve content production and high digital renovation. The suggested approach improves the cultural heritage recognition systems while creating more accurate personalized MR experiences.

Conclusions

The MR applications enable cultural heritage accessibility to individuals through digital enhancing features and interactive historical reconstructions. ICH includes oral traditions, performing arts, and rituals that were at risk of fading due to modernization and limited preservation methods. Digital preservation techniques frequently fall short in providing a completely immersive portal of ICH and lack multi-modal integration. The audio, text, and image datasets of cultural heritage were collected from Kaggle. Data pre-processing techniques include noise reduction, tokenization, and data augmentation to improve the data quality. Feature extraction was performed by using CNN for audio, visual data and Word2Vec for textual data, ensuring an accurate understanding of cultural expressions. The extracted features are then fused at the feature level, integrating multiple data modalities for a coherent and enriched representation of ICH. The processed data was integrated into an MR environment by using platforms like Unity and Unreal Engine, allowing real-time interaction through gesture recognition and voice-based controls. To provide adaptable and high-fidelity digital reconstruction, the suggested approach of the BPNN algorithm was utilized to improve content production. The suggested method is implemented by using Python 3.10.1. The proposed approach is evaluated based on realism, cultural authenticity, system performance, and knowledge retention rate, demonstrating MR-driven ML models that significantly enhance the accessibility, preservation, and educational impact of ICH.

Limitations and Future Scope

The high quality of MR experiences was costly and it requires talented artists and developers to plan and execute; smaller cultural organizations might find it difficult to invest. Complex cultural customs and behaviours might be oversimplified or misrepresented when intangible cultural material was translated into virtual format. Future scope could require more cooperation between local communities, developers, and cultural groups to guarantee MR representations that accurately capture the spirit of intangible cultural heritage.

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