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ORIGINAL

Preservation of Cultural Heritage Buildings in Central Plains via Novel Detection Approach

Preservación de edificios de patrimonio Cultural en las llanuras centrales a través de un nuevo enfoque de detección

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ABSTRACT

Modern nations recognize cultural heritage as an expression of culture and variety. Conserving and repurposing historic buildings has only been more popular in the last decades. Nonetheless, a considerable portion of cultural legacy is afflicted by structural concerns that endanger the safety of buildings and people. Challenges include a scarcity of resources, whether financial, human, or material. This initiative aims to employ deep learning (DL) approaches to preserve cultural heritage buildings, particularly in poor nations where these buildings are still being maintained. To overcome these issues this study proposed a novel Flower Pollination improved Resnet (FP-IResNet) to detect preservation of cultural heritage buildings. The image data were collected from China's cultural heritage buildings. The data is preprocessed using normalization. Histogram of Oriented Gradients (HOG) using extract the features for preprocessed data. The proposed method is implemented using Python software. The findings reveal that the suggested obtained greater performance in the detection of cultural heritage buildings than other traditional algorithms. The suggested concept enables the computerized preservation of cultural heritage buildings, leading to improved accuracy and reduced individual fault. Performance measures show that the model is successful in correctly categorizing and detecting heritage buildings that require preservation, with high accuracy (96,82 %), precision (97,21 %), recall (97,58 %), and an F1 score (93,58 %). The research emphasizes how computerized techniques could enhance the precision and effectiveness of CH conservation initiatives.

Keywords: Cultural Heritage Buildings; Preservation; Histogram of Oriented Gradients (HOG); Flower Pollination improved ResNet (FP-IResNet).

RESUMEN

Las naciones modernas reconocen el patrimonio cultural como una expresión de la cultura y la variedad. La conservación y restauración de edificios históricos ha sido más popular en las últimas décadas. Sin embargo, una parte considerable del legado cultural está afectado por problemas estructurales que ponen en peligro la seguridad de los edificios y las personas. Los desafíos incluyen una escasez de recursos, ya sean financieros, humanos o materiales. Esta iniciativa tiene como objetivo emplear enfoques de aprendizaje profundo (DL) para preservar los edificios del patrimonio cultural, particularmente en las naciones pobres donde estos edificios todavía se mantienen. Para superar estos problemas este estudio propuso una nueva polinización floral mejorada de Resnet (FP-IResNet) para detectar la preservación del patrimonio cultural de los edificios. Los datos de las imágenes fueron recogidos de los edificios del patrimonio cultural de China. Los datos son pretratados por medio de la normalización. Histograma de gradiorientados (HOG) usando extraer las características de los datos preprocesados. El método propuesto es implementado usando software Python.

Los hallazgos revelan que la propuesta obtuvo mayor rendimiento en la detección de edificios de patrimonio cultural que otros algoritmos tradicionales. El concepto propuesto permite la preservación computarizada de los edificios del patrimonio cultural, lo que lleva a una mayor precisión y la reducción de la falta individual. Las medidas de desempeño muestran que el modelo es exitoso en categorizar y detectar correctamente edificios patrimoniales que requieren preservación, con alta precisión (96,82 %), precisión (97,21 %), recuerdo (97,58 %) y una puntuación F1 (93,58 %). La investigación enfatiza cómo las técnicas computarizadas podrían mejorar la precisión y efectividad de las iniciativas de conservación de CH.

Palabras clave: Edificios de Patrimonio Cultural; La Conservación; Histograma de Gradiorientados (HOG); Mejora de la Polinización de Flores ResNet (FP-IResNet).

INTRODUCTION

The concept of cultural heritage has changed in step by the overall advancement in management. The characterization of heritage is very broad and encompasses equally tangible cultural heritage (TCH) and intangible cultural heritage (ICH). Archaeological finds, monuments, and collections of artifacts are all covered in the former.[1] These include performing arts, social conventions, oral traditions and expressions, rituals and festivals, knowledge and practices related to the natural environment, outer space, and the information and abilities necessary to create conventional craft. It is significant to communicate that this classification of ICH is preliminary.[2] Several regional variations are practiced in certain nations, including customs related to food, pilgrimage, animal husbandry, traditional plays and sports, and remembrance sites. It is employed in a variety of contexts, including scientific research, chronological museums, intellectual centers, and educational settings.[3]

One way to advance this process is through the utilization of diverse 3D technology. To access cultural heritage items that are hard to come by in the real world. Documentation, protection, modernization, reinstallation, management, diffusion, and dispersion are the fields of research that fall under the umbrella of preservation.[4] Information storage of all kinds is related to documentation. Protection is defined as taking steps to prevent harm, destruction, or other cultural heritage losses. The process of visualizing cultural heritage items to aid in comprehension is known as reconstruction. Reconstruction, retouching, infilling, integration, and replacement of non-original features are among the tasks that make up restoration. The area of conservation is to prolong the existence of cultural assets while bolstering the legacy's important ideas and ideals. Dissemination is the use of contemporary technology to represent and visualize TCH and ICH objects.[5,6,7,8]

In general, material culture has a far longer lifespan than intangible culture. Heritage buildings are fundamental to the concept of tangible cultural heritage. Modern technology combined with traditional craftsmanship is used in the preservation of these buildings.[9] Understanding and preserving the integrity of these buildings is made possible by strategies including building strengthening, temperature management, and the application of non-invasive techniques like ground-penetrating radar and laser scanning.[10] Memories and experiences are frequently lost to time or conveyed incorrectly. Indigenous culture is also lost as a result of changes in civilization. For this reason, preserving non-material culture for future generations is a crucial endeavor at the moment.

The principal aim was to automatically identify newly built building areas (NCBAs) while simultaneously exploring the potential to use ZY-3 high-resolution images from satellites to pinpoint the date of their alteration.[11] They suggested a three-part automated technique for detecting changes, to enhance the properties' temporal consistency; they first jointly identify the NCBAs using traits that are planar-vertical. Finally, they captured the NCBAs and the change timing concurrently by using a model for multi-temporal change detection. To summarize the highest and best uses (HBU) of buildings in chronological order, the authors develop a creative and economic assessment model that will take into account the preservation of the buildings' original image and integrity, as well as their social, cultural and economic character.[12]

The strategy of integrating classification model into Historical building information Model (H-BIM) using J48 algorithm is analyzed.[13] Investigated whether city morphological components that influence the strength of culture within city regions were constant or exhibit distinct daily variations with geographical dispersion, employed ridge regression and Light GBM using large-scale multi-source spatial information.[14] Additionally, this research broadens the consideration of the types of heritage places and offers hypothetical justification for city planning, economic growth, and cultural preservation. A deep object-based semantic change detection framework for evaluating structural damage.[15] Instead of using the superpixel segmentation that is typically employed in the traditional Object-based Image Analysis (OBIA) framework, they employed an unfathomable objective localization network to produce precise building objects to smoothly merge OBIA and deep learning (DL).

To promote the development of an as-built with intricate structural deformations, modeling techniques that are not widely available in the field of science were developed.[16] A deep-learning-based unique two-level objective recognition, measurement, and segmentation technique for large-scale structures was proposed by the author.[17] It was carried out to compare the effectiveness of the suggested approach using Mask R-Convolution Neural Network (CNN) and a full convolution system, used in others researches.[18,19,20] Using a two-level approach based on DL, this is the first attempt to mechanically sense, the sector, with an evaluation of extensive minor deterioration on ancient structures.

Problem statement

- Real-time monitoring systems are often absent from heritage buildings, which increases the chance of irreparable damage and delays the identification of structural problems.
- The subtle damage indications that are often missed by traditional manual inspections could be detected more accurately and preserved.

METHOD

The image-based data were collected and this data was pre-processed by a global normalization approach and its resizing, Augmentation, and Grayscale Converted the cultural image data and processed in the Conditional Random Field (CRF) layer. Then these normalized image data are represented in each pixel by using a Histogram of Oriented Gradients (HOG) and these feature vectors can be used as input for flower pollination-improved ResNet (FP-IResNet) models. To accurately identify and classification of structural issues in cultural heritage buildings, generate detailed reports on their condition, and increase classification and building defect detection, this study uses combining approaches IResNet and FP optimization. Figure 1 represents the Methodology flow.

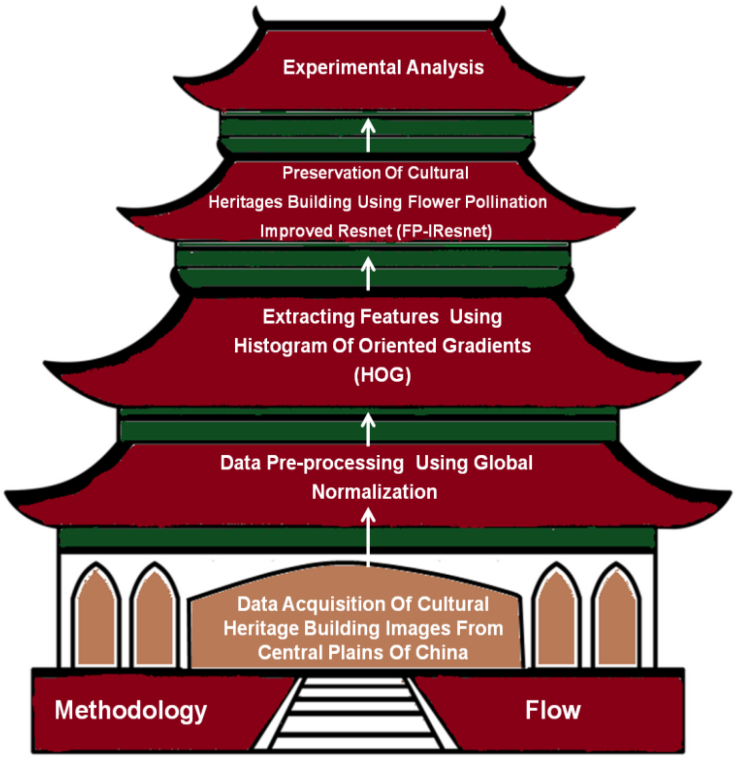

Figure 1. Methodology flow

Acquisition of data

The image data were collected from China's Central Plains, which are home to a large number of historically significant sites. Examples as: the Shaolin Temple, the Longmen Grottoes, the White Horse Temple, the Kaifeng Iron Pagoda, and Yinxu. Innovative detection and conservation techniques are necessary to preserve these heritage monuments' cultural images and importance. Additionally, these monuments must be protected from environmental threats like earthquakes, humidity, weathering, pollution, and human interference. Preservation techniques like structural reinforcement, anti-seismic upgrades, rock stabilization, timber preservation, and corrosion prevention are essential in this regard. To guarantee that these cultural treasures survive and be appreciated by future generations, regular upkeep, and restricted access are necessary. These old buildings embody historical and cultural narratives. Figure 2 represents the variety of cultural heritage places in the central plains of China.

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Figure 2. Cultural heritage central plains in China

Data pre-processing (Globally normalization)

After the acquisition of the data, it was included in the pre-processing of data, using Global normalization. In this study , the preprocessing of the cultural Image data are Resizing, Augmentation, and Grayscale Conversion processed in the CRF layer. It anticipates receiving feedback in the form of class scores. To transfer the presentations' $g_y \in R^{Gy}$ to a vector u_y of the size of the output classes $M=M_{FD}+M_{QF}$, first apply a linear layer (see equation 1).

$$v_y = X_y^S g_y \qquad (1)$$

Using $X_y \in R^{Gy\times M}$, the input sequence for the CRF layer in a phrase classification challenge isn't always obvious. Consequently, suggest using the following score sequence to describe the combined entity and relation categorization issue (see equation 2).

$$c = [v_{FD}(f1), v_{QF}(q_{12}), v_{FD}(f_2)] \qquad (2)$$

Where q_i represents the relationship between f_j and f_i, accordingly, and estimates the combined probability often of the types S_{f1}, S_{f2} and the relations Q_{f1}, Q_{f2} as follows (see equation 3):

$$O(S_{f1}Q_{f1f2}S_{f2}) \approx O(S_{f1}).O(Q_{f1f2}\backslash S_{f1}).O(S_{f1}\backslash Q_{f1f2}) \qquad (3)$$

It seems that there is more dependency between relations and entities than there is between the two entities. The CRF layer calculates the following core given a series of predictions z after padding its input of length n=3 with begin and end tags (see equation 4):

$$T(z) = \sum_{j=0}^{m} P z_j z_j + 1 \sum_{j=1}^{m} c_{j,_{z_j}} \qquad (4)$$

The transition score from class l to class k is denoted by $R_{l,k}$, while the class r score at position p in the sequence is represented by $c_{o,p}$. Since every variable in the CRF layer exists in the log space, the scores are added together. During training, the transition score matrix $P\in R^{(M+2)\times(M+2)}$ is discovered. To determine the log probability of the right label sequence z, the forward algorithm calculates the scores for each potential label sequence Z during training (see equation 5).

$$\log\big(o(\hat{z})\big) = \frac{f^{t}(\hat{z})}{\sum_{\hat{z}\in Z} f^{T(\hat{z})}} \qquad (5)$$

Viterbi is used in testing to determine which label sequence z* has the highest score (see equation 6):

$$z^{*} = \underset{\tilde{z}\in Z}{\arg\max}\, t\,(\widetilde{z}) \qquad (6)$$

The outcome of this process is a set of pre-processed and normalized cultural image data.

Extracting features using Histogram of Oriented Gradients (HOG)

After preprocessing data, it was included to extract the features using HOG. The HOG method's basic idea is to use gradient data gathered from each pixel to derive differentiating characteristics for heritage building image detection. HOG characteristics are often extracted using the various window sizes of the heritage building image. The heritage building image's window is split into many blocks in the initial HOG method, and each block is further broken into multiple cells. For instance, every block includes four cells, and every cell could have sixteen (4 × 4) pixels.

The HOG method begins by computing the gradients of every pixel in every cell, or, to phrase it another way, by utilizing the surrounding pixels to calculate the inverses in both the horizontal and vertical directions. The image's gradient is calculated as equation (7) and (8) demonstrate:

$$H_w(W,Z) = \mathrm{I}(w+z,1) - \mathrm{I}(w-z,1)1 \qquad (7)$$
$$H_y(W,Z) = \mathrm{I}(w+z,1) - \mathrm{I}(w-z,1) \qquad (8)$$

Where H_y is the gradient of the vertical path, H_w is the gradient of the horizontal direction, and I(w,z) is the heritage building image pixel with coordinates w and. The subsequent stage of the HOG method is to determine every pixel's amplitude and position after determining gradients, as seen in (9) and (10):

$$Magnitude(,z) = \sqrt{H_w^2(w,z) + H_z^2(w,y)} \qquad (9)$$
$$Orientation(,z) = tan^{-1}(H_z(w,y)/H_w(w,y)) \qquad (10)$$

The HOG technique's third phase, the binning task, involves creating a histogram predicated on the estimated direction of every cell's pixel, which, based on the software's settings, can range from 0 to 180 or from 0 to 360 degrees. By adding weighted significance to neighbouring bins depending on the direction position to the centre, pixel significance is added to bin direction data to minimize aliasing. The outcome is a set of feature vectors, each representing an image pixel in terms of its HOG descriptors. These feature vectors can be used as input for FP-IRes-Net models.

Detecting the preservation of cultural heritage buildings using Flower Pollination Improved ResNet (FP-IResNet)

Extracted data were utilized to detect the preservation of cultural heritage buildings using FP-IResNet, and this process combines two approaches.

Improved Res-Net (IResNet)

It provides precise categorization from images, which improves the preservation of buildings with cultural value. Processes for assessment and repair can be automated and streamlined with the help of its strong design. Many residual buildings are stacked together to create an FP-IRes-Net. A residual block illustration is provided. Formally, each residual block is defined as follows (see equation 11):

$$W^{[k+1]} = \begin{cases} ReLU\left(\mathcal{F}\left(W^{[k]},\left\{W_j^{[k]}\right\}\right) + W^{[k]}\right), & if\ Size\left(\mathcal{F}\left(W^{[k]},\left\{W_j^{[k]}\right\}\right)\right) = size\left(W^{[k]}\right); \\ ReLU\left(\mathcal{F}\left(W^{[k]},\left\{W_j^{[k]}\right\}\right) + W_o^{[k]}W^{[k]}\right), & if\ Size\left(\mathcal{F}\left(W^{[k]},\left\{W_j^{[k]}\right\}\right)\right) \neq size\left(W^{[k]}\right); \end{cases} \qquad (11)$$

ReLU is the activation function; $F(W^{[k]}, \{W_j^{[k]}\})$ is a learnable residual mapping function that can have several layers, for example, $F=W_j^{[k]}$ for a bottleneck FP-IRes-Net with three layers. Where $W^{[k]}$ and $W^{[k+1]}$ are the inputs and output vectors of the k-th FP-IRes-Net. A learnable linear projection matrix $F=W_j^{[k]}$ ReLU($W_2^{[k]}$ ReLU($W_1^{[k]}$ W));$W_O^{[k]}$ is capable of mapping the size of $w^{[K]}$ to the output size of F. This function is only available when there are no matching dimensions to execute the element-wise addition between Fand $w^{[K]}$. Figure 3 represents the IRes-Net model.

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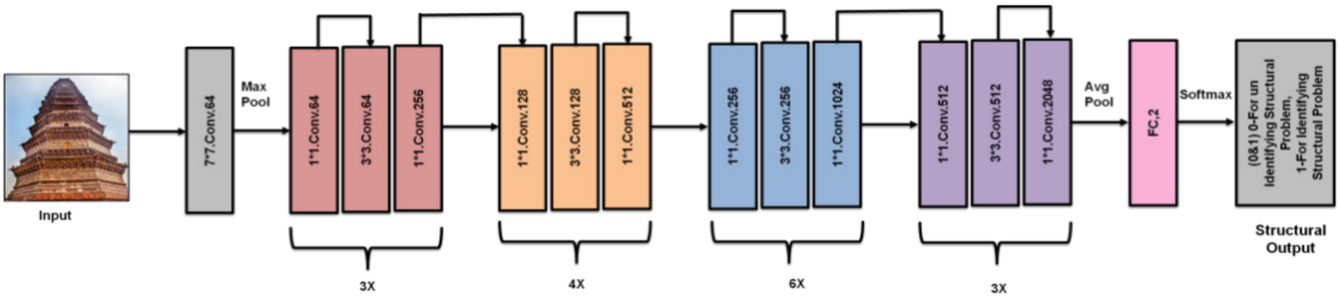

Figure 3. IResNet model

IRes-Net was designed specifically to make it simple for information to flow both forward and backward across the network. Three convolution layers, three batch normalizations, and three ReLU layers make up the original FP-IResNet bottleneck. The large gray arrow in the original Improved ResNet denotes the quickest route for information to spread, including the shortcut connection. Nonetheless, the major propagation path has a ReLU activation function, as seen in equation (11). Due to the ReLU's zeroing of the negative signal, information propagation could be adversely affected. This is particularly important in the early stages of training since the network could potentially begin adjusting the weights to provide a positive signal that is unaffected by going through a ReLU. IResNet accurately identifies and classifies the structural issues in cultural heritage buildings, generating detailed reports on their condition.

Flower Pollination (FP)

To increase classification and building defect detection, this study uses FP optimization of the IResNet model parameters and accurateness in cultural heritage buildings while accelerating convergence and improving generalization. The FP is a nature-inspired metaheuristic optimization method that emulates the pollination process of flowers. There are two forms of pollination, Self-pollination is the progression by which flowers of the same type fertilize one another by spreading pollen from one blossom to another that is identical. Cross-pollination is the process by which insects like birds, bees, and bats carry pollen from one plant to another over great distances. It is noteworthy to remark phenomenon known as floral constancy, wherein certain insects tend to visit certain flowers without visiting others. Based on the idea that the longest-distance-traveling insects are the fittest, the mathematical model of global pollination and floral constancy is explained as follows (see equation 12):

$$\vec{w}_j^{s+1} = \vec{w}_j^{s} + \gamma^k\left(\vec{w}_j^{s+1} - \vec{w}^*\right) \quad (12)$$

Where w_j^{s+1} expresses the next position, k is a step created based on the levy distribution, γ is the step size scaling factor, s denotes the current iteration, w_j^{s+1} represents the ith solution's current location, and w* is the best-so-far solution. Although the subsequent is a depiction of the mathematical representation of local pollination (See equation 13):

$$\vec{w}_j^{s+1} = \vec{w}_j^{s} + \epsilon\left(\vec{w}_l^{s} - \vec{w}_i^{s}\right) \quad (13)$$

In the scenario where a uniform distribution between 0 and 1 yields a random value for the variable, two solutions, w_l^s and w_i^s , were selected at random from the current population. By combining the FP Approach with the FP-IRes-Net, classification accuracy is improved by utilizing the precision of the optimization technique and the resilience of the DL model. This synergy improves overall model performance and decision-making by enabling the more precise and effective detection of cultural heritage building elements.

RESULTS

The study analyzes the efficiency of preserving cultural heritage buildings, particularly in developing countries where such preservation is still conducted. FP-IResNet was suggested to identify buildings that are part of cultural heritage. The preservation detection was evaluated according to these criteria (recall, accuracy, precision, F1 score).

Accuracy

Accuracy is the percentage of all analyzed buildings that are accurately classified as heritage buildings, including both those that require preservation and those that require not. It shows how well the innovative detection method determines the actual condition of buildings designated as cultural property.

$$Accuracy = \frac{Truepositive + Truenegative}{Totalnumberofobservation} \quad (14)$$

Precision

The preciseness of the number of buildings designated as needing preservation is measured by precision. It's the proportion of accurately recognized positive findings of heritage buildings that require preservation to the total number of positive results that were discovered.

$$Precision = {}^{True\ positive}/_{True\ positive + False\ positive} \quad (15)$$

Recall

Recall is used to assess how successfully the detection algorithm finds all historically significant buildings that are truly in need of preservation. It is the proportion of all real positive instances to all correctly detected positive findings (heritage buildings needing preservation).

$$Recall = \frac{True\ positive}{True\ positive + False\ negative} \quad (16)$$

F1 score

It's a statistic that creates a balance between recall and accuracy by combining the two. It is especially helpful when you have to balance accounting for false positives and false negatives. The F1 Score is the choral mean of recall with accuracy.

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (17)$$

The FP-IResNet model's performance metrics are shown in table 1 and figure 4 to protect culturally significant buildings. With an accuracy of 96,82 %, it demonstrates a high level of overall categorization accuracy. The model's precision of 97,21 % indicates how well it can identify buildings that need to be preserved. The model's 97,58 % recall rate indicates that it can accurately identify the majority of the buildings that need to be preserved. The model's balanced performance in detecting and accurately classifying heritage buildings is highlighted by the F1 score of 93,58 %, which combines precision and recall into a single statistic.

Table 1. Preservation comparison

Proposed (FP-ResNet)	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
	96,82	97,21	97,58	93,58

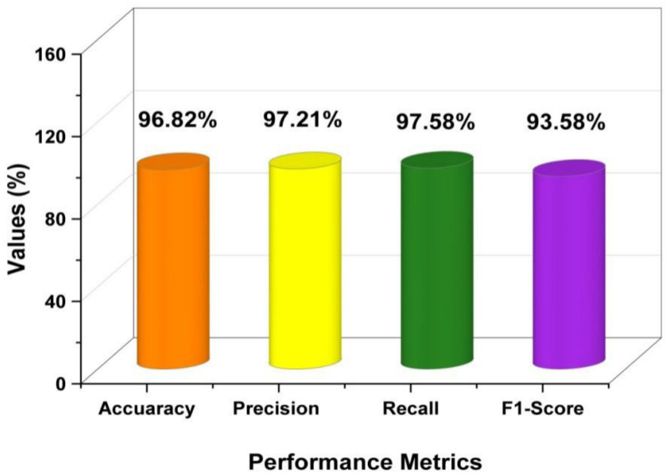

Figure 4. Performance metrics for proposed FP-IResNet

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Figure 5 demonstrates the training loss graph to assess the suggested model's estimated reliability. After 26000 steps in iterations, the training loss value gets closer to 0,2. A number nearer zero signifies a greater degree of similarity with the real value; hence, the algorithm's estimation reliability can be deemed to be adequate.

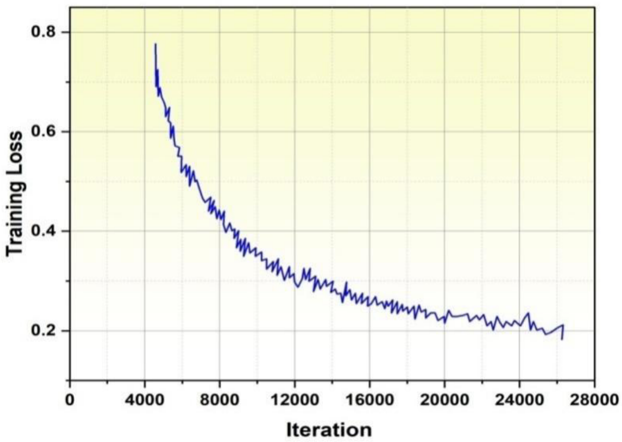

Figure 5. Training loss for FP-IResNet

DISCUSSION

The J48 algorithm automates heritage intervention decision-making in an H-BIM[12] model, increasing productivity and cutting down on assessment time. Its dependence on predetermined classifications, however, could make it less flexible to the various viewpoints of interdisciplinary teams engaged in the decision-making process. Ridge regression and LightGBM[13] were used to evaluate huge geographical data from multiple sources to ascertain how consistently urban morphological aspects impact the health of urban and heritage places. It does, however, show that the elements affecting vitality vary throughout various places, emphasizing the necessity of customized approaches to urban growth and cultural conservation. Using applications for bitemporal high-resolution spatial sensor imagery, the OBIA-CNN[14] framework is combined to provide a single semantic change detection system framework to improve disaster response time and accuracy in building damage assessment. Nevertheless, its application to different crisis scenarios or image quality circumstances could be limited due to its dependence on particular deep learning architectures. A unique two-level approach that greatly increases the efficiency of evaluating superficial damage on large-scale structures by using Mask R-CNN for damage segmentation and measuring and Faster R-CNN[16] for object detection. However, generalizability to other kinds of historic materials or constructions could be limited due to its dependence on certain deep learning models and the caliber of training data. This study suggested a unique FP-IResNet for identifying preservation needs in cultural heritage structures to overcome these constraints. It improves decision-making agility and flexibility by taking into account the various viewpoints of interdisciplinary teams.

CONCLUSIONS

The study introduces FP-IResNet, a revolutionary DL technique, to progress the maintenance of cultural inheritance buildings in China's Central Plains. The strategy tackles the obstacles caused by structural issues and resource constraints. Performance measures show that the model is successful in correctly categorizing and detecting heritage buildings that require preservation, with high accuracy (96,82 %), precision (97,21 %), recall (97,58 %), and an F1 score (93,58 %). Research emphasizes how computerized techniques could enhance the precision and effectiveness of cultural heritage conservation initiatives.

The main drawbacks of the FP-IResNet model are its dependence on high-quality, varied datasets, whose capacity limits its generalizability, and the substantial processing computing resources needed, which might not be accessible in all environments. To increase the model's applicability, it should concentrate on customizing it for different architectural styles and geographical areas, incorporating it with other conservation technologies like 3D scanning and augmented reality, and creating real-time monitoring systems to support prompt and proactive preservation efforts.

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