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A Novel Optimization Approach for Revolutionizing Architectural Design in Chinese Cultural Heritage

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Abstract

The preservation of China's cultural heritage architecture, which combines contemporary and ancient building techniques, is difficult because of the aesthetic and structural degradation that has overtaken it. This architecture is a testament to the country's technical, artistic, and cultural achievements. A smokescreen with a resolution of 5192 × 4153 pixels was used to acquire surface photographs and ground shots of the Dazu Rock Carvings, Nanchan Temple, and Foguang Temple using the Microtrans Maryland 4-1000 program. The research aims to improve fault analysis in images of Chinese cultural heritage structures using an Ensemble Ant Colony Fused Convolutional Capsule Neural Network (EAC-CCNN). Then, using a combination of Augmented Reality (AR) and Building Information Modeling (BIM), the designing model for safety management and decision-making will be enhanced. Steps include collecting and annotating data, developing a hybrid EAC-CCNN model to probe the issue with the architectural building, training the model, connecting it with BIM, inspecting the site, and then analyzing the defects using augmented reality (AR) enhanced BIM models. The results show that this integrated approach works to increase the accuracy of defect identification, promote cooperation, and help maintain and preserve cultural heritage assets. The machine learning model's ability to detect and classify defects in buildings that are considered part of China's cultural heritage is evaluated using metrics such as accuracy and F1 score. "With an F1 Score of 95.47% and an accuracy of 93.29%, the architectural design fault identification and safety management model produces respectable results. Phases of training, validation, and testing measure performance in relation to project objectives. Using this approach, machine learning models may be taught to see patterns, fix errors, and make wise predictions under different conditions.

Keywords: Architectural Design; Cultural Heritage; Building Information Modeling (BIM); Machine Learning; Ensemble Ant Colony Fused Convolutional Capsule Neural Network; Augmented Reality(AR).

1. Introduction

Since its foundation, China has been vigorously implementing programs to safeguard cultural heritage. Aspects of China's multi-pronged strategy include physical protection, historical and social context, and aesthetic philosophy. Preserving China's illustrious cultural heritage is of the utmost importance. Since China's cultural legacy is more than the sum of its pieces, this movement seeks to protect all of it. Understanding the many interrelated components of China's architectural legacy is crucial to appreciating this facet of the nation's cultural legacy [1]. The term "cultural heritage" is used to describe a group's accumulated set of cherished, long-standing activities, rituals, beliefs, locations, artifacts,

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and traditions. Cultural legacy may be both material and intangible, as stated by the International Council on Monuments and Sites (ICOMOS). Records, books, objects, and pictures are examples of artifacts; agricultural, coastal, and rural landscapes are examples of natural habitats; and archaeological sites and city ruins are examples of the constructed environment. The cultural heritage of a country is a good barometer of its level of civilization. In the past ten years, Westerners' views on contemporary Chinese architecture have shifted. The rapid urbanization of China has given architects more freedom to be inventive, creative, innovative, and free-spirited. With their analytical and creative problem-solving skills, architects help people cope with these surges in change. Architects have an active role in the design of new spaces that serve as powerful tools for research, documentation, and preservation since they rely on traditional concepts and methodologies [2].

The rich and intriguing cultural heritage of China may be better preserved for the sake of future generations if specialists from many domains work together [3]. Ancient Chinese structures stand head and shoulders above the rest of human civilization's architectural and cultural achievements. It came into being via a tangled network of traditional, modern, and socially conscious notions. According to UNESCO[4], as of July 2021, China has 56 sites, including 38 WCHS, making it the second-highest number of World Heritage Sites (WHS) globally.

Use of virtual reality technology to study ancient Chinese architecture may substantially enhance research into traditional Chinese culture, national beliefs, and related topics [5]. Traditional materials, such as books, paintings, and photographs, have played an essential role in depicting ancient Chinese architecture. Preservation refers to the deliberate process of safeguarding cultural artifacts from one generation to the next. Modern museums, cultural centers, scientific institutions, and educational institutions all make use of it [6].

Nevertheless, as a society that fully embraces digital technology, the use of digital photography, the internet, and three-dimensional (3D) models has transformed the way historical architecture is studied and presented. Collaboration between the Palace Museum and BIM allowed for the creation of a 3D model of the Forbidden City [7]. Google Earth's B3D Virtual Rome and France's BVirtual History ROMA are two more recent examples of good virtual presentations of historical structures powered by the Unity engine. The performances are made possible by virtual reality (VR) technology and incorporate the interior spaces, visual aspects, and virtual study of historic structures. It is only recently that we have had the means to display past construction methods and architectural styles [8]. No amount of computer-generated imagery or animation can live up to the current requirements for the authoritative presentation of ancient Chinese architecture [9]. People are trying to get the word out about how beautiful old Chinese architectural designs are, both inside and out.

1.1. Key Contributions

- Integrating modern technologies such as BIM, AR, and EAC-CCNN is crucial for academics to detect defects in Chinese cultural heritage buildings.
- To identify typical issues such as black crust cracking, corrosion-induced separation, horizontal breaking, patterned breaking, diagonally breaking, material degradation, structural vulnerabilities, building oxidation, or design errors, an algorithm known as EAC-CCNN analyses photos.
- A digital depiction of infrastructure and buildings, Building Information Modeling (BIM) allows architects and engineers to create three-dimensional models of structures with accurate details about materials, components, and spatial connections. By combining EAC-CCNN with BIM models, designers may see detected issues in context with the overall building plan.
- By superimposing digital data and virtual components, augmented reality improves the user experience and helps construction professionals, engineers, and architects grasp flaws and their safety consequences more effectively.
- The authenticity, uniqueness, and safety of cultural heritage buildings may be guaranteed by this all-encompassing method of architectural design.

1.2. Difficulties

- Problems with Generalizability: Although our model performs admirably on the datasets we examined, we have not yet conducted sufficient study to ascertain whether it may also be utilized for considerably different architectural styles or for historic structures in a state of disrepair. Because of this, the model's applicability to broader preservation projects may be affected.
- Training Data Sensitivity: The efficiency of the EAC-CCNN model is greatly affected by the precision and diversity of the training data. Underrepresentation of certain architectural types in the dataset can lead to skewed model predictions.

1.3. Challenges

- Research limitations are highlighted by the insufficient data from flying Microdrones Maryland4-1000 over Chinese historical monuments and taking surface images at each station. This highlights the necessity for ongoing cultural heritage activities to improve future studies and promote model generalizability.

1.4. Research Gaps

- Despite CaffeNet's widespread use in computer vision applications, the popular deep learning framework has certain drawbacks that make it difficult to apply for architectural design fault diagnosis and safety monitoring.
- Among these are issues with interpretability, a shallow network architecture, and a heavy demand on computational resources. This research aims to address and prove the necessity for better, more accessible, and less resource-intensive methods in this field.

This work is organized into sections: 2 deals with related work, 3 with materials and methods, 4 with results and discussion, and 5 with a conclusion.

2. Related Works

The authors, approaches, and results of several research on computational optimization techniques and architectural design are summarized in Table 1.

Table 1. Summary of Related Works

Ref	Proposed	Methods	Result
Harifi et al. (2021) [10]	In order to find the optimal architectural design solutions quickly, accurately, and efficiently, the study recommended using the Giza Pyramids Construction (GPC) method, a population-based metaheuristics approach.	GPC algorithm	Among the many optimization problems that the GPC method can solve, it stands apart from the competition. The benchmark test functions and picture segmentation both make use of it.
Wang et al. (2022) [11]	With the goal of offering an automated solution, the displacement discusses traditional Chinese architecture and demonstrates how to use Historic-Building-Information-Modeling to create a regular axis from irregular column grids (HBIM). In order to create a straight axis from irregular grids, Historic-Building-Information-Modeling-Finite Element Modeling (HBIM-FEM) is used.	HBIM-FEM	This approach resolves relocation problems in traditional Chinese buildings at a World Heritage Site in Qufu, Shandong, China, demonstrating its repeatability and responsibility.
Wei (2024) [12]	Using Building Information Modeling (BIM) software, this study develops a programme that integrates contemporary architectural practices with traditional Chinese elements. This strategy was put into action when a specific testing location was selected.	BIM Digital Technology	According to the research, the building's wide range of vivid colors enhances the allure of traditional architectural details by 35.42 percent.
Baduge et al. (2022) [13]	This article takes a look at how the construction industry is utilising AI, ML, and DL. It focuses on smart operation, durability, health monitoring, architectural design, materials, and the circular economy.	AI- ML and DL	Not only does the study provide useful information to researchers, practitioners, and stakeholders in the construction industry, but it also tackles problems with model generation and highlights the importance of data in the building lifecycle.
Liu et al. (2020) [14]	A new approach to assessing and forecasting public building energy consumption was presented in the study (PBs). It is based on the technology known as Support Vector Machine (SVM). Data collected from June to September is used to search for anomalies in the energy consumption of air conditioners in the Wuhan-focused study.	SVM	Results showed that they were responsible for 38% of total building energy use. The study shows that there were four days in September when air conditioning demand was quite high, which could be a sign of problems and lend credence to efforts to reduce emissions and increase energy efficiency in the future after Paris.
Chen et al. (2024) [15]	Examining the difficulties in maintaining cultural elements, this paper investigates how contemporary urban development in Henan, China, has interacted with traditional cultural and opera architectural styles.	10 inhabitants of Henan participated in semi-structured interviews to elicit their viewpoints and experiences.	The study accomplished its aims of illustrating how architectural designs for cultural and opera stages in Henan, China are influenced by urban and commercial influences.
Roman et al. (2020) [16]	This article discussed how Building Performance Optimization (BPO) can be used to enhance thermal comfort and energy efficiency during the design phase of multi-story buildings. A different model generated by an artificial neural network is utilized by the application to reduce computing time (ANN).	BPO-ANN	Using performance assessment criteria, four multi-objective algorithms are evaluated to determine the optimal approach and parameter values.
Yu et al. (2020) [17]	The research investigates the difficulties involved in training and building deep neural networks. It focuses on automated Hyper-Parameter Optimization (HPO) and assesses its accuracy and efficiency.	HPO-DNN	The paper evaluated the effectiveness and precision of model evaluation techniques, outlining problems, solutions, toolkits, and services that are available for evaluating models with constrained computing resources.
Liu et al. (2021) [18]	The inverted design issues and promoting scientific research in areas including quantum physics, organic chemistry, medical imaging, and photonics and optics, the paper demonstrates the revolutionary influence of machine learning in these sectors.	ML and DL	The study focused on DL techniques that addressed structural design problems with large degrees of freedom. It also emphasizes the quick progress made in ML-enabled photonic design strategies.
Jiang et al. (2023) [19]	Computational optimization is presented in this study as an application for AAD (Automatic Architectural Design).	AAD	To improve the robustness and efficiency of building renovation design, ensuring the layout meets facility needs and aligns with sustainability goals.

No workable solution for recognizing architectural and cultural field flaws was provided by the aforementioned methodologies outlined in the linked publications. Therefore, in order to find the flaws in the design of Chinese cultural heritage buildings, this research suggested a new optimization method. When it comes to finding architectural design flaws, this suggested methodology provides a safety management system and fault analysis.

3. Material and Methods

In order to detect damage in Chinese cultural heritage architecture, the EAC-CCNN is utilized in this research. While CapsNet can withstand affine distortions, EAC-CCNN is more effective in picture identification. Using these methods in the field of architectural design allows for the creation of digital models of buildings. By combining augmented reality with building information modeling, a comprehensive safety management model may be created. This study's flow diagram is shown in Figure 1. Not only does this approach simplify decision-making and safety planning, but it also offers accurate fault detection and categorization.

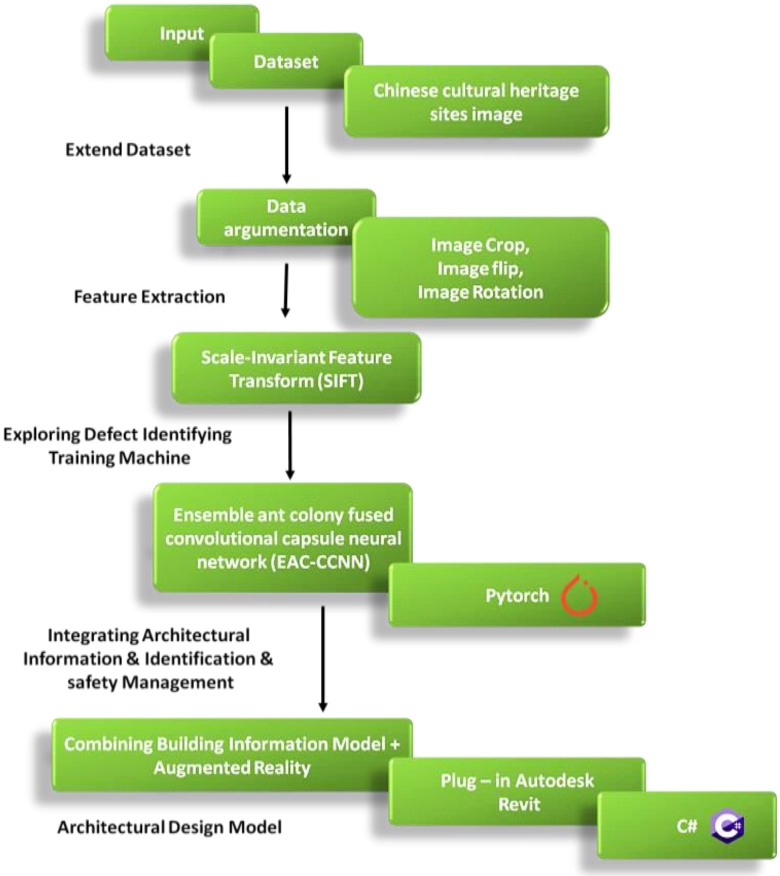

Figure 1. Proposed model

3.1. Image Data Collection

The examination took place by flying Microdrones Maryland4-1000 over Chinese historical landmarks [20] and capturing surface images at each station, using an instructor test as a guide. Four flight routes were available: one for nadir bullets and three for 45° orthogonal images. The largest possible picture dimension was 5192 by 4153 pixels. Thanks to the Gigapan Epic Pro's settings—which comprised a pitch range of -60° -60°, step 40°, and a yaw range of 0°-320°, step 40°—every site was able to capture 45 surface photographs". The acquired aerial photographs of the ground reached a resolution of 3940 × 4620. In Figure 2 you can see the pictures from the dataset.

Figure 2. DatasetImages ((A) Dazu Rock Carvings, (B) Nanchan Temple and (C) Foguang Temple)

3.2. Image Preprocessing

One method of deep learning (DL) is picture augmentation, which primarily involves training neural networks with previously taken photos by applying various modifications to them. The diversity of the dataset used for training is therefore enhanced. Three common techniques for image enhancement are random flip, random cut, and random rotation. It is possible to make an inverted version of an image by randomly inverting its vertical or horizontal orientation. The model's robustness against changes in item sizes and positions is enhanced by using random crop. This technique introduces variability in the position and scale of important objects, such as building defects, making the model more accurate. By introducing an arbitrary angle of rotation into the picture, random rotation makes the model more resistant to changes in object orientation. Image enhancement increases variation, fortifies the model's resistance to changes in object orientation, position, and size, and makes it easier for the model to apply assumptions to new data when trained on a larger range of situations.

3.3. Feature Extraction

Scale-Invariant Feature Transform (SIFT) and other DL methods aid in picture detection. EAC-CCNN is trained for image recognition applications using the TensorFlow and PyTorch packages. Permutation is defined by the augmented reality experience's complexity. The local energy metric in picture fusion quantifies the prominence of features in a certain damaged region. All the pixels in a specific area have their squared intensities added up for the calculation. When combined, the native power and the frequencies of Spatial Multiresolution Analysis (SMA) enhance details while maintaining picture quality. In GIS, object recognition, feature extraction, and picture compression, geographical multiresolution means looking at data at different levels using techniques like pyramid-based representation, multiscale segmentation, and wavelet treatments. What is the indigenous power?

$$KF(c,d) = \sum_{n,m=-1}^{1} x(n,m) D_{i_o}^{2}(w+n, z+m) \tag{1}$$

By assigning weights to each pixel in a local neighborhood, the low-frequency coefficient of a source picture is determined by the window weight matrix in the layer. Thanks to this matrix, which determines the contribution of each nearby pixel, the fusion rule can be adjusted to your liking.

$$x(n,m) = \frac{1}{15}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 3 & 2 \\ 1 & 2 & 1 \end{bmatrix} \tag{2}$$

Characterized low-frequency combination scheme.

$$D_{i_o}^{E}(c,d) = \begin{cases} D_{i_0}^{A}(c,d) KF_{i_o}^{A}(c,d) > KF_{i_o}^{B}(c,d) \\ D_{i_0}^{B}(c,d) KF_{i_o}^{A}(c,d) > KF_{i_o}^{B}(c,d) \\ 0.5 \times \left(D_{i_0}^{A}(c,d) + D_{i_0}^{B}(c,d)\right) \, other \end{cases} \tag{3}$$

A fusion picture F and two source images A and B are described in the notation for a fusion process. SML is a method for fusion logic that uses several source images with different resolutions to obtain relevant data while preserving image quality and reducing artefacts. It is the SML.

$$SML_{i,j}(c,d) = \sum_{n=-N}^{N} \sum_{m=-M}^{M} ML_{j,i}(c+n, d+m) \tag{4}$$

where $ML_{j,i}(c,d)$ is the separate form of the Lagrangian and (2P+1) (2Q+1) is the window size. The defective phrase is explained as follows:

$$ML_{j,i}(c,d) = \left|2D_{i,1}(c,d) - D_{i,1}(c-t,d) - D_{i,1}(c+t,d)\right| + \left|2D_{i,1}(c,d) - D_{i,1}(c,d-t) - D_{i,1}(c,d+t)\right| \tag{5}$$

where $D_{i_0}^{E}(c,d)$ stand for the variable separation between pixels and the coefficient of determination value of the high-frequency signal subband that was positioned after the Discrete Cosine Transform (DCT) decomposition. A description of the SML-based high-energy combination arrangement follows:

$$D_{i,k}^{E}(c,d) = \begin{cases} D_{i,k}^{A}(c,d) SML_{i,k}^{A}(c,d) \geq SML_{i,k}^{B}(c,d) \\ \quad D_{i,k}^{B}(c,d) \quad other \end{cases} \tag{6}$$

The following areas have unique incorporation Stage:

Stage 1: Apply DCT decomposition on source image A in order to retrieve frequency coefficients.

Apply DCT decomposition to source picture B in order to retrieve frequency coefficients.

Stage 2: To combine low-frequency coefficients for each high- and low-frequency sub-band coefficient, use fusion criteria based on local energy. Fusion rules based on SML should be utilized for high-frequency coefficients.

Stage 3: To get the fusion coefficients $D^E_{i_0}(c,d)$, and $D^E_{i,l}(c,d)$combine the fused coefficients.

Stage 4: Applying the inverse DCT transform, reconstruct the fusion coefficients. Use the inverse DCT technique to reconstruct fusion image F.

Incorporating automatic component grouping, real-time communication, error detection, and visualisation for informed decision-making, the image proposes an interactive method for gathering, constructing, and visualising components for complex systems or structures. The method also ensures precise and seamless outcomes.

3.4. Ensemble ant Colony Fused Convolutional Capsule Neural Network (EAC-CCNN)

The application of capsule networks, often known as CapsNets, is a novel approach to studying and localizing structural defects. The purpose of this study is to investigate the errors in photographs of Chinese cultural heritage using a method called EAC-CCNN, which achieves robust classification. In order to identify images, CNNs use convolutional and pooling layers. The complex spatial linkages to capsules, which are groups of neurons that represent entity attributes and keep geographical order, are recorded by CapsNets. Figure 3 shows the CCNN architecture in action, which employs a CNN model for feature map extraction in the outset and CapsNet for classification. After CNN extracts preliminary feature maps using pre-trained models, CapsNet analyzes them to generate a final classification result.

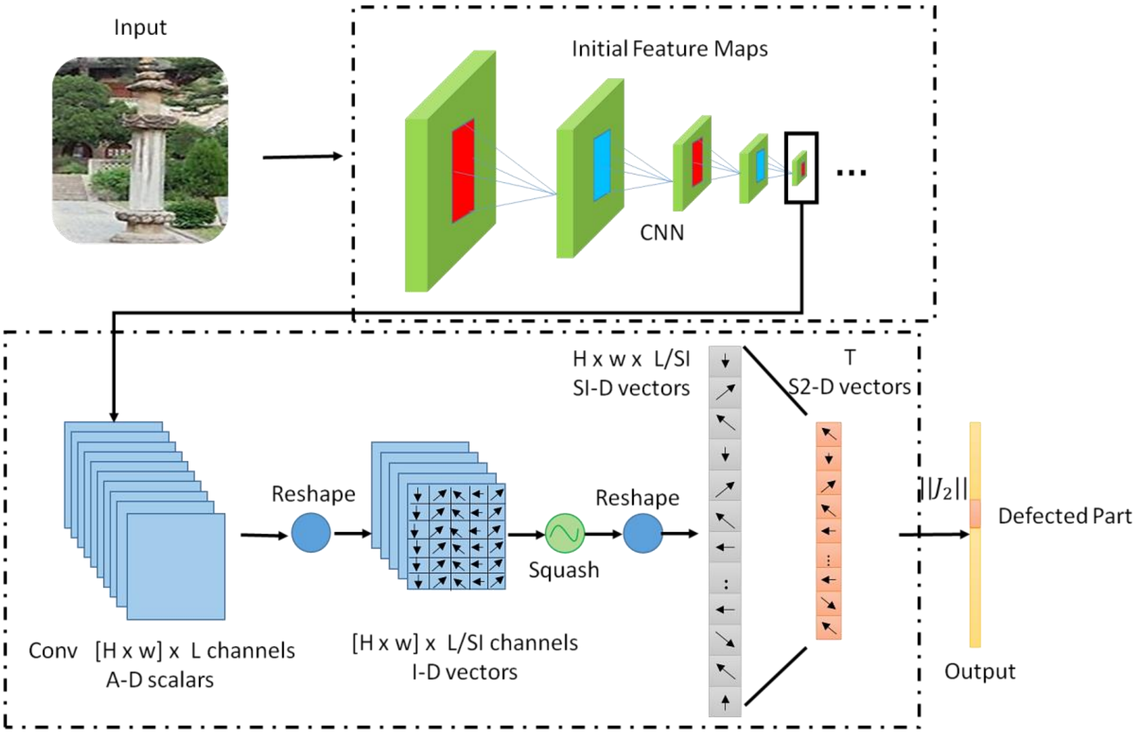

Figure 3. CCNN Architecture

Over the course of the two training phases, CNN parameters are set to a frozen state, and CapsNet weights are established. To find the coupling coefficients between capsules, the dynamic routing method is used. By combining the feature extraction capabilities of CNN with CapsNet's spatial connection learning, the proposed method enhances the classification accuracy of remote sensing photographs. In the first of two stages of training, the CCNN components are fine-tuned; in the second, testing, the learned model is put to use for classification on data that has not been observed. For complex patterns with spatial interconnections, this approach excels. The "capsules" used by CapsNets are groups of neurons that keep track of various object properties. To understand the three-dimensional character of faults, the networks are able to maintain spatial linkages. Through dynamic routing, lower-level capsules are able to communicate with and vote on the instantiation parameters of higher-level capsules.

The convolutional neural network (CCNN) is a dynamic routing method that predicts how higher-level capsules will act by using lower-level capsules. “You can see the interconnection between the various level capsules in Figure 4. This process is necessary for learning picture-based spatial links and part-whole hierarchies.

$$\hat{v}_{i|j} = X_{ji} v_j \tag{7}$$

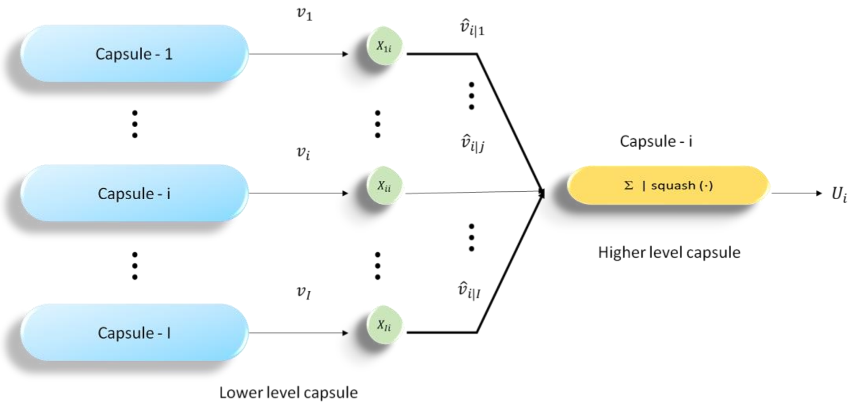

Figure 4. Network Connection

A X_{ji} weighted sum, The process includes calculating the input vector, a nonlinear squash function, and the coupling coefficient. By measuring the degree of agreement between the expected and actual SoftMax output, the routing technique is executed repeatedly for numerous iterations, updating the coupling coefficients.

$$d_{ji} = \frac{\exp(a_{ji})}{\sum_l \exp(a_{jl})} \quad (8)$$

CapsNets employ a logarithmic likelihood variable called a_{ji} to decide whether, to combine two capsules of different sizes. By increasing the parameter from 0 to a value that is in good agreement, the coupling coefficient can be found. By compressing short and big vectors, respectively, and by recognizing output computational vectors as probabilities, the nonlinear squash function of CapsNets guarantees stability throughout training.

$$c_i = \sum_j d_{ji} \hat{v}_{i|j} \quad (9)$$

Dynamic routing relies on the agreement u_i between predicted and actual outputs b_{ji} of capsules, affecting coupling-coefficients d_{ji} and improving information routing over the Capsule Network.

$$u_i = \frac{||t_i||^2}{1+||t_i||^2} \frac{t_i}{||t_i||} \quad (10)$$

$$b_{ji} = \hat{v}_{i|j} u_i \quad (11)$$

Optimization of the network's parameters and hyper-parameters for each capsule in the last layer is done to reduce loss. Capital Neural Networks are designed with three layers:

$$k_l = S_l \max\left(0, m^+ - ||u_l||\right)^2 + \lambda\, (1 + S_l \max\left(0, ||u_l|| - n^-\right)^2 \quad (12)$$

Principal and final caps for convolution. Due to its dynamic routing mechanism, CapsNets can learn complex spatial connections and aid in object and feature detection within images. The final image caps are shown in Figure 5.

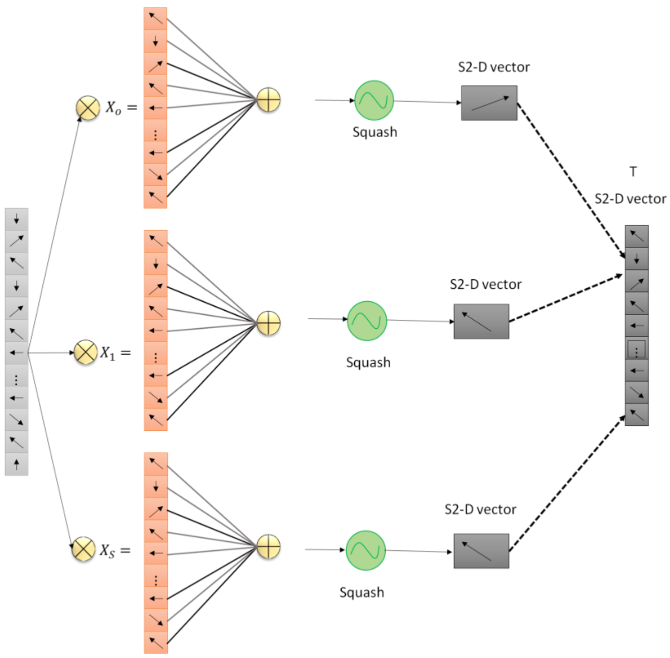

Figure 5. Final Caps

When it comes to finding various patterns in structural defects, CapsNets shine because of how well they capture part-whole hierarchies. Using popular DL frameworks such as TensorFlow and PyTorch, it is possible to apply CapsNets and integrate libraries. In order to construct a CapsNet architecture specifically for defect identification, it is essential to create capsules that encode relevant features pertaining to corrosion, separation, and cracking. One metaheuristic optimization method that enhances AR/BIM integration is Ant Colony Optimization (ACO), which uses CapsNet-based image processing. Image grid processing operations such as segmentation, registration, filter selection, parameter tweaking, texture generation, and compression EAC-CCNN optimization can be facilitated by ACO, an adjustable tool. This is illustrated in Figure 6.

The following applications make use of pheromone trails: picture registration, optimization of object suggestions, filter selection, evaluation of feature relevance, and image reduction techniques. It aids in dynamic adaptability, multi-agent coordination, feature selection, resource allocation, registration, and route planning for detection and classification tasks.

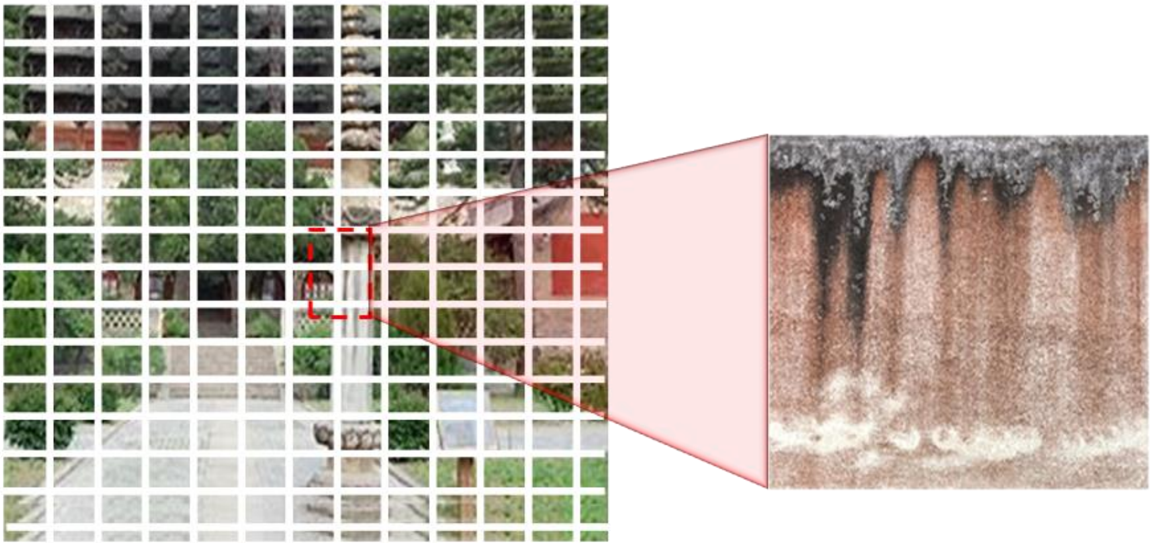

Figure 6. EAC-CCNN Models

3.5. Integration of Building Information Modeling and Augmented Reality

Building information modeling (BIM) and augmented reality (AR) provide an all-encompassing answer to the problems of building information management by allowing users to organize, visualize, and interact with building data. Building information modeling (BIM) provides a central repository for a suite of building data, including material properties, engineering characteristics, and design specifications. With the help of sensors, computer vision, and image processing, augmented reality technology creates a living, breathing virtual environment while enhancing the display of architectural data.

The integration of augmented reality (AR), computing power, and image processing software opens up new possibilities for blending the virtual and actual. With the ability to participate in real-time and track in three dimensions, stakeholders can now interact with building information. By checking that it matches the real context, an environment fusion module guarantees that the digital data is accurately depicted as building data. Better decision-making, teamwork, and project sustainability are all outcomes of combining building information modeling (BIM) with augmented reality (AR). This approach takes static project management and turns it into a visual, interactive, and dynamic experience that improves collaboration, decision-making, and the longevity of the project. Tools from Autodesk's Revit program can be utilized for image detection in building information modeling and augmented reality.

Using Ant Colony Optimization to train a CNN-Capsule model for improved picture classification results is demonstrated in Pseudocode 1. After importing libraries and loading picture data, the model architecture is established, the data is split into training and validation sets, the model weights are changed, and finally, the model is evaluated.

Pseudocode 1. EAC-CCNN pseudocode

```
importnumpy as np
importtensorflow as tf

defcreate_capsule_network(input_shape, num_classes):
num_ants = 10
num_iterations = 100
pheromone_matrix = np.ones((num_connections,))  # Initialize pheromone levels
pheromone_evaporation_rate = 0.1
α = 1.0
β= 2.0

for iteration in range(num_iterations):
for ant in range(num_ants):
solution = initialize_random_solution()
fitness = evaluate_solution(solution)
while not stopping_criteria_met:
probabilities = calculate_probabilities(pheromone_matrix, solution, alpha, beta)
            selected_connection = np.random.choice(num_connections, p=probabilities)
solution = update_solution(solution, selected_connection)
            new_fitness = evaluate_solution(solution)
            update_pheromones(pheromone_matrix, selected_connection, new_fitness)
        save_best_solution(solution, fitness)
    update_global_best_solution()
    pheromone_matrix *= (1.0 - pheromone_evaporation_rate)
best_solution = get_global_best_solution()
print("Best solution:", best_solution)
```

4. Result and Discussion

Using augmented reality and building information modeling, a method for fault identification in Chinese cultural heritage pictures was developed. This method digitalizes CapsNet, builds a model for safety management, and finds architectural flaws.

In order to create digital models for the purposes of investigation, modeling, and visualization, the methodology employs CAPS net scanning techniques. Using EAC-CCNN algorithms, we were able to train an identification model that could detect structural abnormalities with an F1 score range of 95.47% and an accuracy of 93.29%. The EAC-CCNN is a machine learning model developed for use in analyzing design flaws and managing safety in Chinese cultural heritage architecture. Measures of accuracy and F1 score are employed to assess the efficacy and offer recommendations". Assessing the technique's performance throughout validation and testing ensures optimal reliability and dependability. Its usefulness can only be ascertained by user feedback and comparative analysis. Consideration of real-world implementation concerns, such as data integration and availability, is essential.

As shown in Figure 7, an oxidation building is an example of an event that was misclassified using the DL model. An add-in was created to link the model to the Revit modeling tool, which allows for rapid identification of anomalies and decision-making. Figure 8 shows the application programming interface (API) and C# code that are used to integrate the Python-developed model into the Revit by Autodesk program.

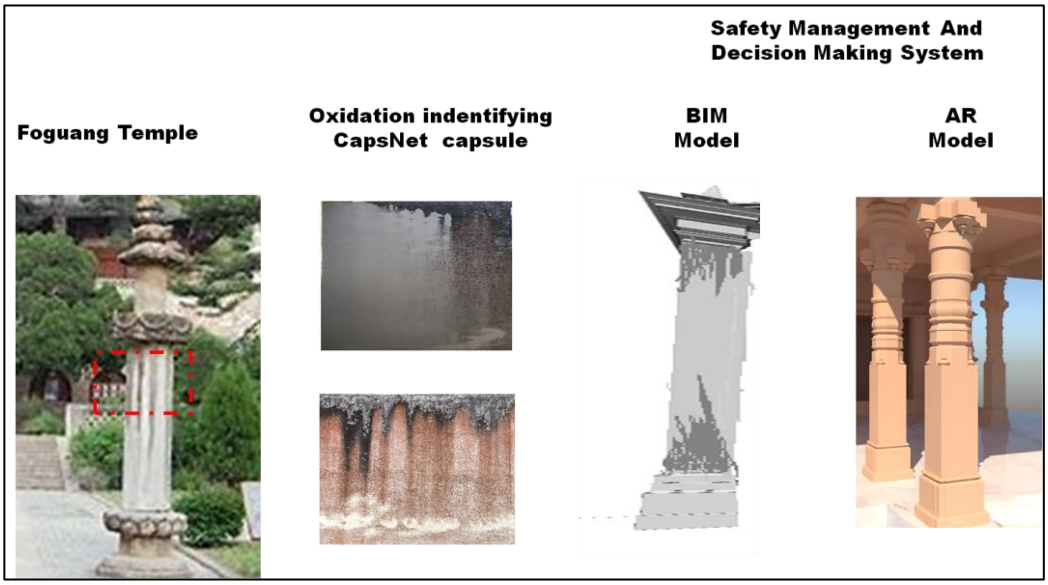

Figure 7. Over Outcomes

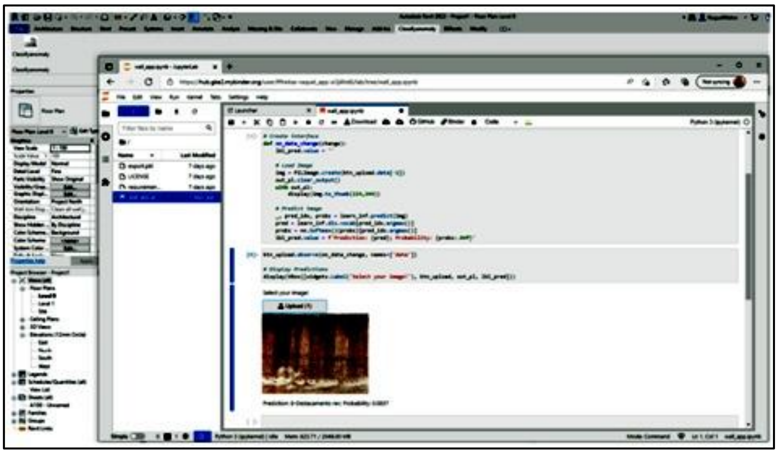

Figure 8. Defect Identifying Model

4.1. Metrics For Performance and Model Evaluation

For the purpose of evaluating the model, the training model is fed images from the test set in order to obtain prediction results. Moving forward, a number of measures are calculated by contrasting these forecasts with the actual labels. This research looks at how well the algorithm model did using a bunch of common measures for evaluating object identification systems. The key metrics include F1 Score, Accuracy, Precision, and Recall. The accuracy, precision, recall, and F1 score were compared to other image processing approaches used for defect identification in Figure 9 and Table 2, respectively. Accuracy, defined as the ratio of correct predictions to total guesses, is the most intuitive metric. In mathematical terms, it is defined as:

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{13}$$

Precision is the percentage of accurate forecasts among all targets that have been projected. The following are the precise formulas:

$$Precision = TP/(TP + FP) \tag{14}$$

Recall indicates the percentage of real targets that the model accurately predicts. The following are the recall formulas:

$$Recall = TP/TP + FN \tag{15}$$

The F1 score finds a good middle ground between the two characteristics by calculating an overall rating based on the linked mean of recall and accuracy. One way to find out your F1 score is by:

$$F1\ score = \frac{2\times TP}{2\times TP\times FP\times FN} \tag{16}$$

Table 2. Evaluation of Safety Management

Optimization Techniques	Criteria for Appraisal (%)			
	Accuracy	Precision	Recall	F1 Score
RFP-Net [21]	91	90.45	90	93
LBP-CNN [22]	78	76	77	74.68
CaffeNet [23]	84.34	83.42	84.12	90.49
EAC-CCNN [Proposed]	93.29	92.13	93	95.47

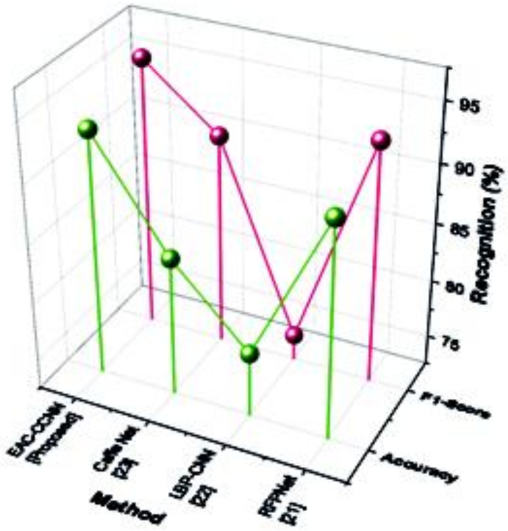

Figure 9. Model Comparison

The goal of a network design known as Region-based Fully Convolutional Networks (RFP-Net) is to evaluate images by zeroing in on key regions [21]. How well it works is dependent on the difficulty level of the damage diagnosis problem and the quality of the training materials. When texture patterns are crucial, LBP-CNN, which combines Convolutional Neural Networks (CNNs) with local binary pattern detection (LBP), is the most suitable visual analysis method [22]. CaffeNet's well-proven architecture and pre-trained models allow it to provide strong baseline performance as a computational vision deep learning model [23]. Instead of using traditional convolutional neural networks (CNNs), Caps-Net can handle data with spatial linkages and structural connections. This is especially helpful when identifying defects or abnormalities in images requires knowledge of the spatial layout of components. Table 2 and Figure 9 show that the proposed method (EAC-CCNN) has the highest accuracy when compared to the current method (93.29%). Figure 10 shows that the proposed model outperforms the baseline in identifying and categorizing complex architectural characteristics in cultural heritage using the dataset, with a 92.13% recall, 93.29% accuracy, 95.47% F1 score, and 92.13% precision and accuracy.

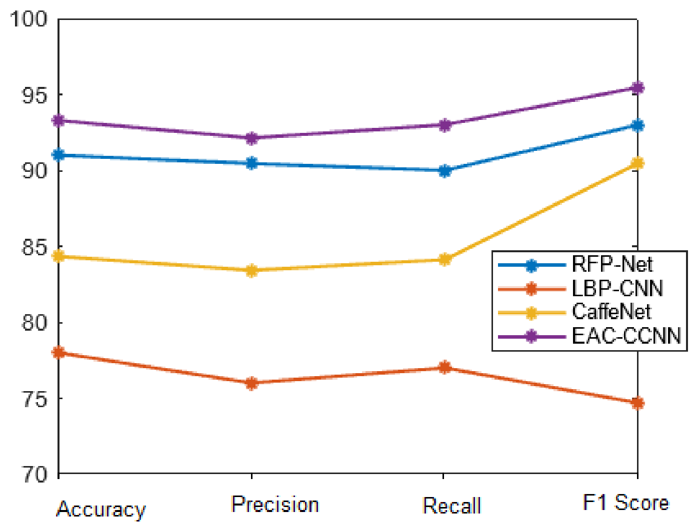

Figure 10. Overall Comparison with Existing methods

4.2. Drawbacks in the Existing Methods

While methods like RFP-Net are helpful, they have limitations when it comes to interpretability, noise sensitivity, and the need for high-quality training data to identify architectural design defects. Accurate results, low processing overhead, and false positives are all possible outcomes of these restrictions. “In addition to its other flaws, RFP-Net has a hard time accurately identifying complicated errors in architectural images. Similarly, generalization is challenging in many contexts for LBP-CNN because it relies too much on local texture patterns to express complicated spatial linkages and structural elements. The method's high processing requirements further restrict its scalability and real-time utility in architectural design contexts. Despite its popularity in computer vision, the famous deep learning framework CaffeNet has limitations that make it unsuitable for architectural design tasks like defect identification and safety monitoring. Its high computing resource requirements, interpretability concerns, and thin network architecture are some of its drawbacks. These limitations show that this area requires better, more efficient procedures that are also more complex and easier to understand.

4.3. To Overcome the Existing Drawbacks Using EAC-CNN

The EAC-CCNN model has greatly improved the process of identifying faults in architectural designs. Combining multiple convolutional and capsule neural networks improves interpretability and noise sensitivity. The requirement for high-quality training data is reduced by the model's capacity to generalize across different architectural contexts and failure types. Better yet, it is able to record complex fault patterns and spatial connections. By reducing computational overhead, EAC-CCNN tackles issues with interpretability and shallow network architecture in architectural design, paving the way for scalability and real-time application.

4.4. Advantage of the Research

This research shows how BIM, AR, and EAC-CCNN are being used to manage and preserve buildings that are part of China's cultural heritage. Decisions in architectural design, safety management, and fault investigation are all improved by this strategy. Enhancing the efficacy of preservation activities, it encourages stakeholders to work together. The method's adaptability and scalability make it possible to make educated decisions about the protection of cultural assets.

5. Conclusion

Cultural legacy, which the Chinese people have preserved and shaped over their lengthy history, is fundamental to both the material and spiritual aspects of Chinese culture. There is a shared cultural heritage among people from all around the world. While some have fallen into disrepair or even been destroyed, others have been revered and passed down through the ages. If we are serious about protecting and developing cultural heritage, we must first understand the bond that exists between individuals and their traditions. Cultural heritage research is an invaluable resource for society since it covers so much ground. Construction safety management could be enhanced by combining augmented reality with building information modeling. Management can track the development of construction projects and spot possible safety hazards with the help of Building Information Modeling (BIM) and Augmented Reality (AR). Experts may help with activities like identifying risks, creating plans to reduce them, creating thorough worker instructions, improving safety procedures, and reducing the chance of accidents on construction sites. This increases the reliability and safety of the projects. It is possible that building damage detection and safety management could be greatly enhanced by combining BIM and AR with an Ensemble Ant Colony Fused Convolutional Capsule Neural Network (EAC-CCNN). With the use of Building Information Modeling (BIM), which compiles information from multiple sources to create detailed models of buildings, EAC-CCNN is able to identify different kinds of damage. The stakeholders can actively engage in the building's health evaluation with the use of augmented reality's real-time visualization. Under these conditions, it is less difficult to organize preventative maintenance, establish plans for proactive maintenance, and enhance protection overall.”. Our improved model has achieved impressive results in recognizing and categorizing complex architectural elements in old buildings, with a recall rate of 92.13%, an accuracy rate of 93.29%, an F1 score of 95.47%, and a precision and accuracy rate of 9.21%.

In the future, we may see initiatives that aim to build interactive visualization tools, incorporate state-of-the-art technologies like LiDAR, expand datasets, validate methods, maintain preservation policies, implement long-term monitoring, and foster community engagement.

6. Declarations

6.1. Author Contributions

X.L. and X.Y. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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