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

Journal of Electrical Systems

Abstract: - Chinese cultural heritage architecture, a blend of traditional and modern construction methods, showcases the country's technological, artistic, and cultural advancements, yet its preservation faces challenges due to structural decay and aesthetic degeneration. Using Microtrans Maryland 4-1000, Dazu Rock Carvings, Nanchan Temple and Foguang Temple smokescreen were captured; surface images and ground photos were captured with smokescreen resolution of 5192 x 4153 pixels. The goal of the research is to use an Ensemble Ant Colony Fused Convolutional Capsule Neural Network (EAC-CCNN) to enhance fault analysis in Chinese cultural heritage structures images, then the combination of Augmented Reality (AR), and Building Information Modeling (BIM) to enhance the designing model for the safety management and decision making. The process entails gathering and annotating a variety of information, creating a hybrid EAC-CCNN model to investigate the architectural building's problem, training it, integrating it with BIM, doing on-site inspections, and utilizing AR-enhanced BIM models to analyze the flaws found. The findings demonstrate how this integrated method improves the precision of flaw diagnosis, fosters teamwork, and aids in the upkeep and preservation of cultural heritage assets. Metrics including accuracy and F1 score are used to evaluate the machine learning model recognizes and categorizes flaws in Chinese cultural heritage architecture. The defect identifying and safety management model of architectural designing outcome of the accuracy is 93.29% and F1 Score is 95.47%. During the training, validation, and testing phases, performance is evaluated by project goals. With the help of this method, machine learning models can be trained to identify patterns, identify flaws, and generate well-informed predictions in a variety of circumstances.

Keywords: Chinese Cultural Heritage, Architecture Design, Augmented Reality (AR), Building Information Modeling (BIM), Ensemble ant colony fused convolutional capsule neural network (EAC-CCNN).

1. Introduction

China has been actively implementing cultural heritage (CH) protection programs since its inception, and China's efforts have a multifaceted approach and focus on understanding historical and sociological contexts, aesthetic ideologies, and physical protection [1]. Since the 1990s, China has been implementing computational methods in cultural heritage studies [2] providing powerful tools for documentation, analysis, and preservation. This interdisciplinary approach contributes to the sustainable preservation of China's cultural heritage for future generations, ensuring the preservation of its rich history and diverse cultural heritage [3]. Ancient Chinese architecture holds a profound place in global architectural history and human civilization. Its existence is an intricate fusion of political, societal, and folk beliefs [4]. Utilizing virtual reality technology to explore ancient Chinese architecture can significantly enhance research into traditional Chinese culture, national beliefs and its related topics [5]. Traditional sources such as books, sketches, and photographs have been pivotal in depicting ancient Chinese architecture [6].

However, we embrace the digital age, the study and presentation of historical architecture have evolved with the use of digital photos, the internet, three-dimensional (3D) models, and other information technologies. The Palace Museum and building information modeling (BIM) worked together to create a 3D Forbidden City [7]. Other recent, effective virtual displays of historical buildings driven by the Unity engine include Google Earth's B3D Virtual Rome and Mondadori's B Virtual History ROMA from France. Virtual reality (VR) technology enables these performances, which showcase the internal areas, visual features, and virtual study of historic buildings. The ability to showcase historical building techniques and architectural styles is relatively new [8]. Existing standards for the professional exhibition of ancient Chinese architecture cannot be fully met by virtual displays or animations of historical buildings and construction techniques [9]. The exterior and interior designs of ancient Chinese buildings are remarkable, and efforts are being made to spread awareness of their beauty.

2. Related Works

Table 1 provides a summary of several works on computational optimization techniques and architectural design, including information on the authors, suggested methodologies, and outcomes.

Table 1: Current Research

Ref	Proposed	Methods	Result
[10]	The study suggested employing the Giza Pyramids Construction (GPC) algorithm, a	GPC algorithm	The GPC technique is a competitive solution provider for a variety of

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	population-based metaheuristics technique that prioritizes efficiency, accuracy, and speed when identifying the best options for architectural design.		optimization issues. It is found in image segmentation and benchmark test functions.
[11]	The displacement concerns Chinese traditional architecture and tries to provide an automated solution by presenting a method for producing a regular axis from irregular column grids in Historic-Building-Information-Modeling (HBIM). It usesHistoric-Building-Information-Modeling-Finite Element Modeling(HBIM-FEM) to construct a regular axis from unequal grids.	HBIM-FEM	The method addresses relocation issues in Chinese traditional buildings at a site designated as a World Heritage Site in Qufu, Shandong, China, proving its reproducibility and accountability.
[12]	In computer research, the Markov chain Monte Carlo (MCMC) approach based on the Bayesian network was applied to examine the impact of Chinese sociocultural influence and French colonialism on the architecture of 68 historic dwellings located in Hanoi's historic Quarter.	MCMC and Bayesian network	The study analyzed how Buddhism influences home façade decorations using Bayesian networks and finds a significant relationship between Buddhist philosophy and beautiful design choices.
[13]	This article examined the use of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in the building and construction industry with an emphasis on smart operation, durability, health monitoring, architectural design, materials, and the circular economy.	AI- ML and DL	In addition to addressing model creation issues, the study emphasizes the critical role that data plays in the building lifecycle and offers insightful information to researchers, practitioners, and stakeholders in the construction industry.
[14]	The study introduced a novel method for diagnosing and predicting energy usage in public buildings (PBs). The method uses the Support Vector Machine (SVM) technology. The study, which focuses on Wuhan, looks for abnormalities in the energy use of air conditioners using data from June to September.	SVM	The study employed the account for 38% of all building energy consumption.The study reveals four high September air conditioning usage days, indicating potential issues and supporting energy efficiency and emission reduction initiatives in the "Post Paris" future.
[15]	The study presented DO_IDS; a new Intrusion Detection System (IDS) intended to improve the accuracy of network security detection of anomalous activities. It uses a hybrid method for data optimization, to improve sample ratio, get rid of outliers, and create an intrusion detection system.	Random Forest (RF), Genetic Algorithm, and Isolation Forest	The UNSW-NB15 dataset examination of the DO_IDS model provides positive results in the detection of unique anomaly behaviors. For intrusion detection systems with few records, this makes DO_IDS a reliable solution.
[16]	The paper presented the use of Building Performance Optimization (BPO) in the design of complex structures to improve indoor thermal comfort and energy efficiency. To cut down on computing time, the program makes use of an alternative model created by an artificial neural network (ANN).	BPO-ANN	To find the best method and ideal value of the parameters, four multi-objective algorithms are assessed using performance assessment criteria.
[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.

[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.
[19]	The paper offers the application of Computational Optimization for Automatic Architectural Design (AAD) and suggests.	AAD	To improve the robustness and efficiency of building renovation design, ensuring the layout meets facility needs and aligns with sustainability goals.

The above methods mentioned in the related works did not provide feasible solution for identifying defects in the architectural and cultural field. Hence, this study proposed a novel optimization technique for identifying the defects in the design of Chinese cultural heritage architecture. This proposed model offers fault analysis and safety management system in identifying the defects in the architectural design.

3. Key Contributions

- For researchers to identify flaws in Chinese cultural heritage architecture, it is essential to integrate contemporary technologies like BIM, AR, and EAC-CCNN.
- A machine learning algorithm called EAC-CCNN examines photos to find common problems like black crust cracking, corrosion-induced separation, horizontal breaking down, patterned breaking down, and diagonally breaking material degradation, structural vulnerabilities, building oxidation or design errors.
- Architects and engineers can generate 3D models of structures with precise information about materials, components, and spatial relationships by using Building Information Modeling (BIM), a digital representation of infrastructure and buildings. Through the integration of EAC-CCNN with BIM models, designers are able to examine and interpret identified flaws in relation to the entire architectural design.
- By superimposing digital data and virtual components over the actual world, augmented reality technology improves how users perceive and engage with physical settings. Architects, engineers, and construction professionals may better grasp the spatial context of defects and evaluate their consequences for safety and functioning by superimposing BIM data and defect analysis results onto real-world views. The integrity and originality of cultural heritage buildings are preserved, and the safety and wellbeing of residents and guests are guaranteed, due to this all-encompassing approach to defect identification and safety management in architectural design.

4. Material and Method

The research uses the EAC-CCNNto identify damage in Chinese cultural heritage architecture. CapsNet are resistant to affine distortions, but EAC-CCNN performs well in image recognition. By using these techniques in architectural design, a digital representation of structures is produced.

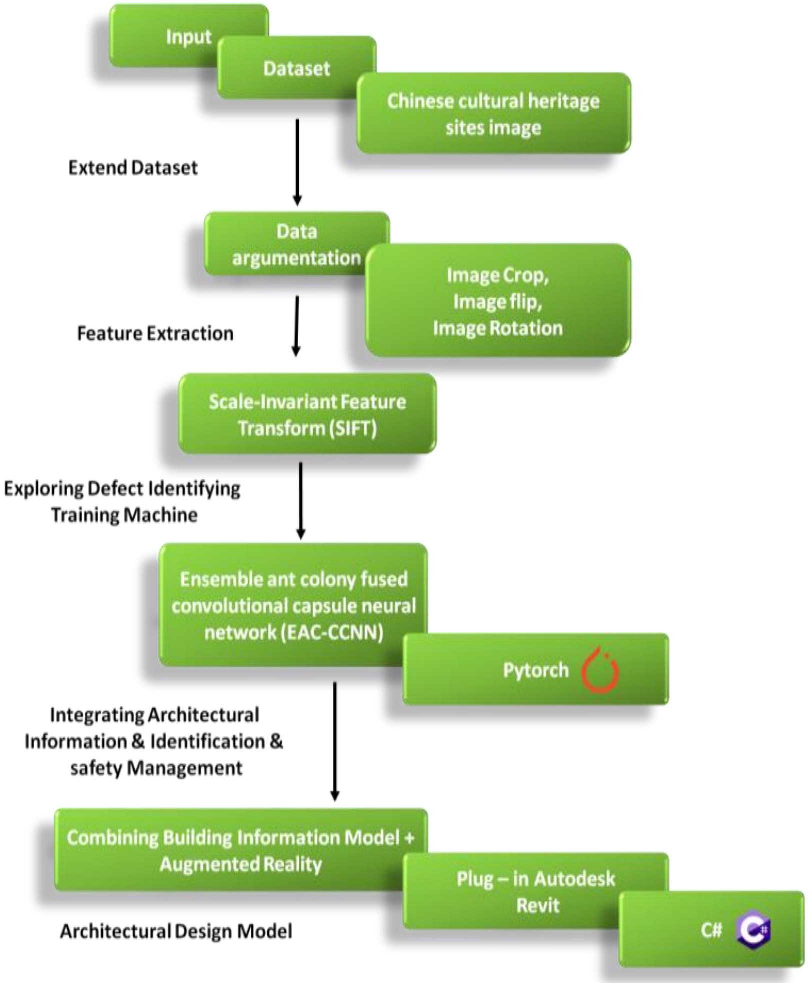

Figure 1: Proposed model

A complete safety management model is produced by integrating AR with BIM technologies. Figure 1 depicts the research flow model. This methodology not provides precise flaw identification and classification, but it also streamlines safety planning and decision-making design.

➢ **Image Data Collection**

Using an instructor test, the investigation comprised flying Microdrones Maryland 4-1000 over historical sites in China [20] and taking surface photos at each station. There were four flight paths: four for 45° orthogonal images and one for nadir bullets. 5192 x 4153 pixels was the maximum dimension of the pictures. Every location was able to collect 45 ground images attributable to the Gigapan Epic Pro's settings, which included a pitch range of -60° -60°, step 40° and a yaw range of 0°–320°, step 40°. A resolution of 3940 x 4620 was achieved in the collected ground photos. The dataset images are shown in Figure 2.

Figure 2: Dataset Images ((A) Dazu Rock Carvings, (B) Nanchan Temple and (C) Foguang Temple)

➢ **Image Preprocessing**

Image augmentation is an approach to deep learning (DL) that applies different changes to pre-existing images, mainly for training neural networks. This increases the variety of the training dataset. Random flip, random crop and random rotation are three popular methods for enhancing images. A picture can be randomly flipped vertically or horizontally to create an upside-down copy of the original. By including random crop, the model becomes more resilient to changes in item sizes and locations by introducing diversity in the position and scale of main objects like defect in the building. To increase the model's invariance to object orientation, random rotation spins the image by a random angle. When a model is trained on a wider range of circumstances, the enhancement of images boosts variation, strengthens its resistance to changes in object orientation, position, and size, and facilitates the model's ability to make assumptions to new data.

➢ **Feature Extraction**

Feature recognition and DL algorithms such as Scale-Invariant Feature Transform (SIFT) image detection approaches. PyTorch and TensorFlow libraries are used to train EAC-CCNN for image recognition applications. The intricacy of the AR experience determines customization. In image fusion, local energy measures how intensely features appear in an individual defective area. The computation involves adding up the squared intensities of all pixels in a certain neighborhood. The indigenous power and Spatial Multiresolution Analysis (SMA) frequencies together improve details and preserve image quality. In image compression, feature identification, object recognition, and Geographic Information Systems (GIS), geographical multiresolution refers to the examination of information at multiple tiers utilizing methods such as multiscale segmentation, wavelet transformations, and pyramid-based representation. The indigenous power is,

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

The window weight matrix in the layer determines the low-frequency coefficient of a source picture by allocating weights to each pixel in a small neighborhood. The fusion rule may be customized due to this matrix, which calculates each pixel's contribution in the immediate area.

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

Characterized low-frequency combination scheme.

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

The notation describes a fusion process using a fusion picture F and two source images, A and B. SML is an approach for fusion logic that gathers data from several source pictures at various resolutions to retain pertinent information while reducing artifacts and maintaining image quality. The SML is,

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

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 $D_{i_0}^E(c,d)$ denotes the coefficient of determination value of the high-frequency signals subband that was positioned $(c.d)$ following the Discrete Cosine Transform (DCT) decomposition, and the coefficient or variable separation between pixels. The high-energy combination arrangement built around SML is explained as follows:

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

The following areas have unique incorporation Stage:

Stage 1: On source image A, do DCT decomposition to extract frequency coefficients.

To extract frequency coefficients for source image B, use DCT decomposition.

Stage 2: Use local energy-based fusion rules to fuse low-frequency coefficients for each corresponding coefficient in the high- and low-frequency sub-bands. High-frequency coefficients should be fused using fusion rules based on SML.

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

Stage 4: Reconstruct the fusion coefficients using the inverse DCT transform. Reconstruct fusion picture F by applying the inverse DCT method.

The image proposes an interactive method for gathering, constructing and visualizing components for complex systems or structures, incorporating automatic component grouping, real-time communication, error detection and visualization for informed decision-making, ensuring precise and seamless outcomes.

➢ **Ensemble ant colony fused convolutional capsule neural network (EAC-CCNN)**

A new method for investigating and locating damages in structures is the use of capsule networks or CapsNets. This research presents a technique EAC-CCNNto accomplishes robust classification for investigating the flaws in the images of Chinese cultural heritage. CNNs employ pooling and convolutional layers to recognize images.

CapsNets record intricate spatial relationships to capsules, which are collections of neurons that reflect entity properties and maintain geographical ordering. A CNN model is used for the initial feature map extraction in the CCNN architecture (figure 3), while CapsNet is used for the classification approach. Using pre-trained models, CNN extracts preliminary feature maps; CapsNet analyzes these maps to produce a final classification outcome.

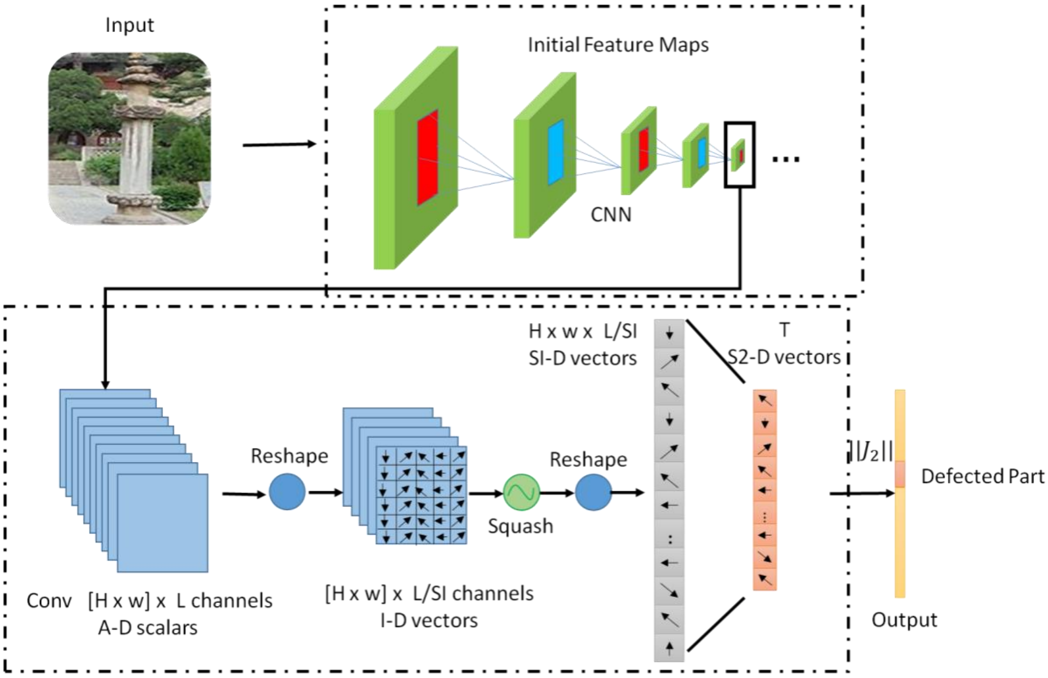

Figure 3: CCNN Architecture

CNN parameters are frozen and CapsNet weights are initialized during the two training stages of the procedure. The coupling coefficients between capsules are determined by the dynamic routing method. The suggested technique improves classification accuracy for remote sensing photos by fusing CapsNet's spatial connection learning with CNN's feature extraction capabilities. The CCNN components are adapted during the two-phase training, and the learned model is applied to unobserved data for classification during the testing phase. This method works well when handling intricate patterns and spatial interactions. CapsNets use capsules, which are collections of neurons that record several attributes of an item. This enables the networks to preserve spatial linkages and comprehend the three-dimensional nature of faults. Capsules in various levels are connected by dynamic routing, allowing them to vote on the instantiation settings of higher-level capsules.

A dynamic routing technique called the CCNN makes use of lower-level capsules i to forecast the behavior of j higher-level capsules. Figure 4 depicts the connectivity of the different level capsules. Learning spatial linkages and part-whole hierarchies in a picture requires this procedure.

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

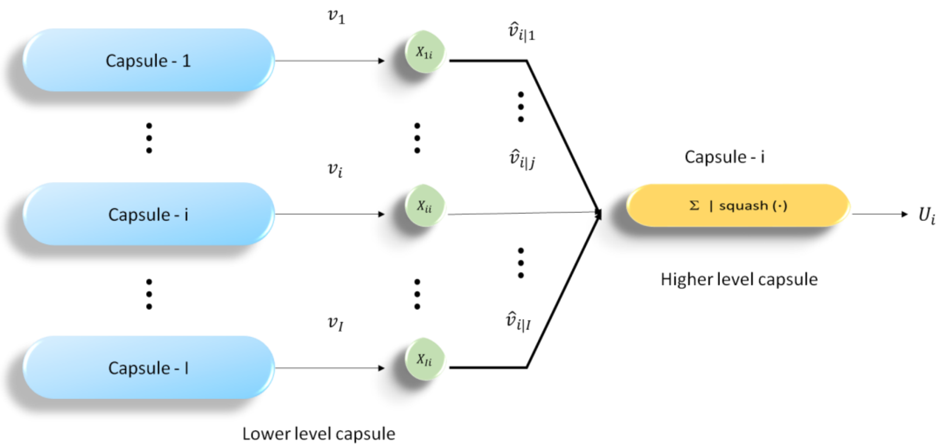

Figure 4: Network Connection

A X_{ji} weighted sum, a nonlinear squash function, the computation of the coupling coefficient, and the input vector calculation are part of the procedure. For several iterations, the routing method is carried out repeatedly, updating coupling coefficients by the degree of agreement between the expected and actual softmax output.

$$d_{ji} = \frac{\exp(a_{ji})}{\sum_l \exp(a_j l)} \tag{8}$$

CapsNets employ a logarithmic likelihood variable called a_{ji} to decide whether, to pair a smaller-scale capsule with a higher-scale capsule. The coupling coefficient is determined by starting the parameter at 0 and increasing with good agreement. The CapsNets' nonlinear squash function ensures stability during training, understanding output computational vectors as probabilities, and preventing them from growing larger than one, compressing short and large vectors respectively.

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

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.

$$u_i = \frac{||t_i||^2}{1+||t_i||^2} \frac{t_i}{||t_i||} \tag{10}$$

$$b_{ji} = \hat{v}_{i|j} u_i \tag{11}$$

To decrease loss hyper-parameters are adjusted and the network's parameters are optimized for each capsule in the final layer. Three layers comprise the CapsNet architecture:

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

Convolution Primary Caps and Final Caps. CapsNets may learn intricate spatial connections and aid in the identification of objects and their characteristics inside an image because of its dynamic routing process. Figure 5 depict the final caps of the image.

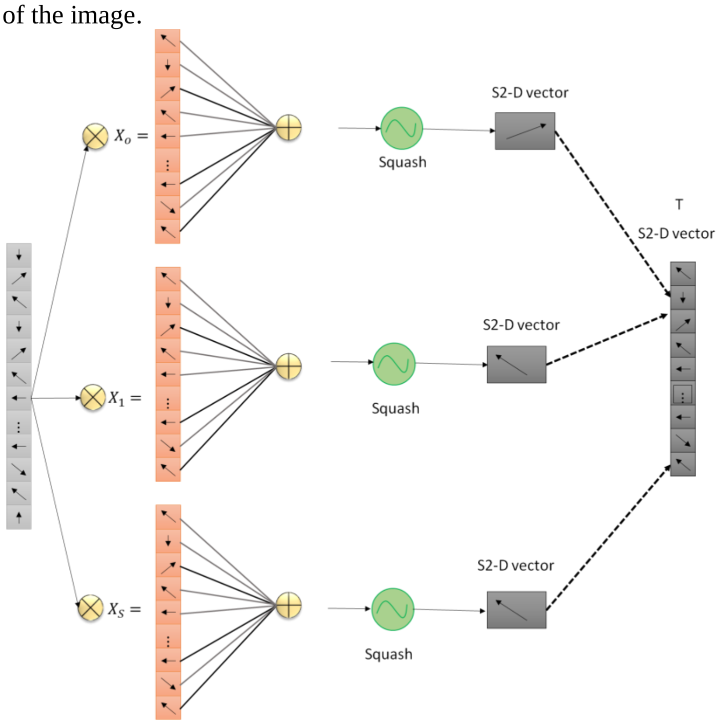

Figure 5: Final Caps

CapsNets are excellent at capturing part-whole hierarchies, which makes them useful for identifying different patterns in structural flaws. It is feasible to integrate libraries and apply CapsNets using well-known DL frameworks like PyTorch and TensorFlow. Creating capsules that encode pertinent characteristics related to corrosion, separation, and cracking is a necessary step in developing a CapsNet architecture tailored to defect detection. Using CapsNet-based image processing, Ant Colony Optimization (ACO), a metaheuristics optimization technique, improves the integration of AR with BIM. An adaptable tool for CCNN image grid processing tasks, ACO aids in segmentation, registration, filter selection, parameter tinkering, texture synthesis, and compression EAC-CCNN optimization in Figure 6. Pheromone trails are used in image reduction techniques, picture registration, object suggestion optimization, feature importance evaluation and filter selection. To ensure effective routes, resource allocation, and feature selection for detection and classification tasks, it helps with path planning, registration, resource allocation, multi-agent coordination, and dynamic adaptation.

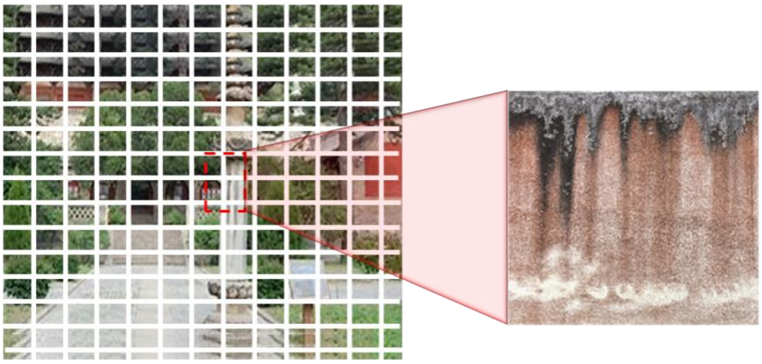

Figure 6: EAC-CCNN Models

➢ **Integration of Building Information Modeling and Augmented Reality**

The BIM and AR offer a comprehensive solution for organizing, visualizing, and engaging with building information, which is redefining building safety management. A centralized repository for a variety of building data, such as material qualities, engineering features, and design requirements, is provided by BIM. Through the use of sensors, computer vision, and image processing technologies, AR technology improves the presentation of building data and produces a dynamic, immersive virtual world. Virtual and physical aspects may be blended into the combination of AR, computer technology, and image-processing software. Stakeholders can interact with building information since real-time engagement and 3D tracking are enabled. An environment fusion module makes sure that the digital data is represented as building data by ensuring that it is in line with the actual context. When BIM and AR are combined, complicated construction information can be shown in an understandable way that improves decision-making, collaboration, and project sustainability. With the help of this method, traditional project management is transformed into a dynamic, interactive and visual experience that promotes better decision-making, teamwork and project sustainability. Image detection in BIM and AR can be used with Autodesk Revit software tools.

Pseudocode 1 illustrates methods to use Ant Colony Optimization to train a CNN-Capsule model for better picture classification results. Libraries are imported, picture data is loaded, the model architecture is defined, the data is divided into training and validation sets, the model weights are updated, and the model is assessed.

Pseudocode 1: EAC-CCNN pseudocode

```
import numpy as np
import tensorflow as tf

def create_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)
```

5. Result and Discussion

The Chinese cultural heritage picture fault identification technique uses AR and BIM to digitalize Caps-net, create a safety management design model and identify defects in architectural design.

Figure 7: Over Outcomes

The methodology uses caps net scanning techniques to generate digital models for analysis, simulation and visualization. EAC-CCNN algorithms were used to create an identification model with 93.29% accuracy and 95.47% F1 Score range for detecting structural abnormalities. A machine learning model called the EAC-CCNN is intended for use in Chinese cultural heritage architecture for fault analysis and safety management in the architectural design. Accuracy and F1 score measures are used to evaluate the effectiveness and provide suggestions. For maximum reliability and dependability, the technique's performance should be assessed during the validation and testing stages. To determine its applicability, comparative analysis and user input are essential. Implementation issues in the real world, including data integration and availability, require being taken into account. An instance of an incorrectly classified phenomenon using the DL model is an Oxidation Building in Figure 7. To connect the model to the Revit modeling program and facilitate efficient anomaly identification and decision-making, "an add-in was developed. The Python-developed model is included into the Revit by Autodesk program through the use of C# programming and asp.NET the application programming interface" shown in figure 8.

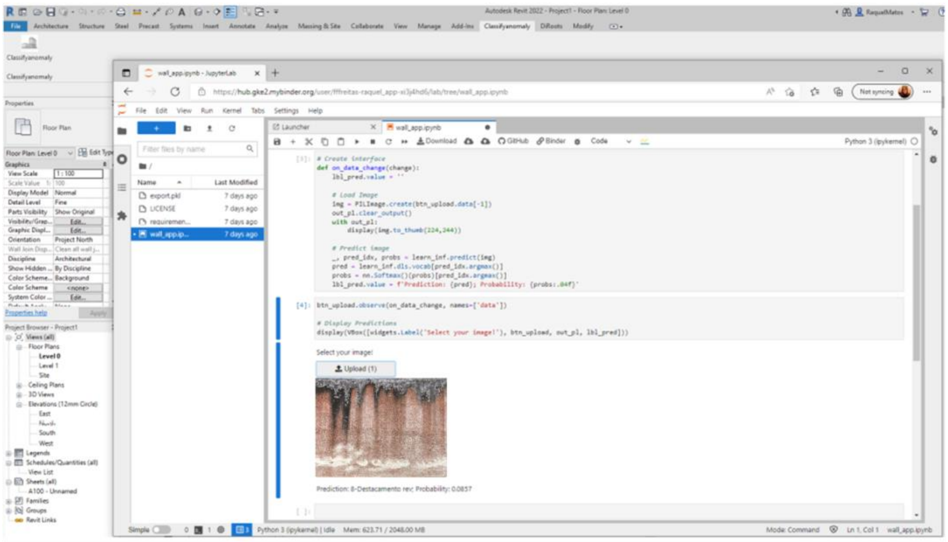

Figure 8: Defect Identifying Model

Figures 9 and Table 2 depict a comparison of the accuracy and f1 Score to the other image processing techniques for the defect-identifying process. The easiest measure to understand is accuracy, which is calculated as the ratio of total right predictions to total guesses. It is described in mathematics as:

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

The F1 score uses the correlated mean of recollection and preciseness to create an overall rating that strikes an appropriate equilibrium between the parameters. The F1 score is determined by:

$$F1\ score = \frac{2\times TP}{2\times TP\times FP\times FN} \tag{14}$$

Table 2: Evaluation of Safety Management

Optimization Techniques	Criteria for Appraisal (%)	
	Accuracy	F1 Score
RFP-Net [21]	91	93
LBP-CNN [22]	78	74.68
CaffeNet [23]	84.34	90.49
EAC-CCNN [Proposed]	93.29	95.47

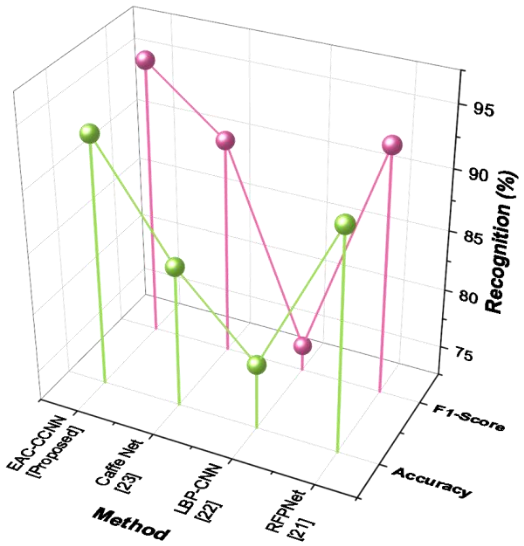

Figure 9: Model Comparison

A network architecture called Region-based Fully Convolutional Networks (RFP-Net) is intended to analyze pictures by concentrating on specific areas of importance [21]. The type of damage identification problem and the caliber of the instructional data determine it performs. For visual analysis, LBP-CNN combines Convolutional Neural Networks (CNNs) with local binary pattern detection (LBP), making it appropriate in situations where texture patterns are important [22]. CaffeNet is a computational vision deep learning model that offers good baseline performance because of its well-proven architecture and pre-trained models [23]. Designed to handle spatial relationships and structural connections in data, Caps-Net is an alternative to regular CNNs. It is particularly advantageous in situations when comprehending the spatial arrangement of elements is essential for recognizing damage or abnormalities in pictures.

- **Drawbacks in the Existing Methods**

Architectural design defect identification is hampered by approaches such as RFP-Net, which, although useful, have drawbacks in terms of interpretability, noise sensitivity, and reliance on high-quality training data. These limitations can lead to erroneous results, false positives, and high computational overhead. RFP-Net's shortcomings are further compounded by its difficulty in properly detecting complex faults in architectural photos. Similar to this, LBP-CNN's reliance on local texture patterns hinders its ability to represent complex spatial connections and structural features, which makes generalization difficult in a variety of settings. Further limiting scalability and real-time usefulness in architectural design settings are the method's high processing needs. Though widely used in computer vision applications, the well-known deep learning framework CaffeNet has drawbacks that make it difficult to use for defect detection and safety management in architectural design. These include its shallow network architecture, interpretability issues, and high computational resource requirements. These shortcomings highlight how this field needs more sophisticated, interpretable, and resource-efficient methods.

- **To Overcome the Existing Drawbacks Using EAC-CNN**

Architectural design fault identification has made significant progress with the introduction of the EAC-CCNN model. Interpretability and noise sensitivity are improved by combining numerous convolutional and capsule neural networks. With its ability to generalize across various architectural contexts and fault kinds, the model lessens the need for high-quality training data. More successfully, it captures intricate fault patterns and spatial linkages. In architectural design situations, EAC-CCNN minimizes computational overhead, resolving interpretability and shallow network architecture problems to enable scalability and real-time application.

- **Advantage of the Research**

The study demonstrates the use of advanced technologies like BIM, AR, and EAC-CCNN in managing and preserving Chinese cultural heritage architecture. This method enhances fault analysis, safety management, and architectural design decision-making. It promotes collaboration among interested parties, boosting the effectiveness of preservation efforts. The scalability and flexibility of the technique facilitate well-informed decision-making on the preservation of cultural resources.

6. Conclusion

Construction safety management could be enhanced by combining AR with BIM. Management can track the development of building projects and detect any safety hazards by using BIM and AR to generate intricate visual representations of intricate construction settings. In the manner of expanding construction safety and dependability, professionals also assist in recognizing and reducing safety risks, illustrating construction procedures, optimizing schemes, early danger detection, and strengthening safety protocols. Safety management and building damage detection may be greatly enhanced by combining BIM and AR with Ensemble Ant Colony Fused Convolutional Capsule Neural Network (EAC-CCNN). The BIM combines data from several sources to create detailed building models; EAC-CCNN is capable of identifying different kinds of damage. Stakeholders can engage with the health of the building through real-time visualization offered by AR. Proactive maintenance planning, preventative actions and general protection enhancement are facilitated by this combination of factors.

Future Scopes

Upcoming projects may focus on developing interactive visualization tools, including machine learning models, integrating cutting-edge technologies like LiDAR, growing datasets, verifying techniques, creating interactive visualization tools, adhering to preservation policies, putting long-term monitoring into place, and encouraging community involvement.

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