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Architectural Heritage Style Identification Using Avian Swarm Optimized K-Nearest Neighbours and Deep Learning

Shenghui Hong
School of Architecture and Urban Planning, Lanzhou Jiaotong University, Lanzhou, Gansu, 730070, China
E-mail: dada9229@126.com

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The architectural heritage style comprises unique design elements and building techniques that are indicative of the historical, social, and cultural milieu of certain eras or locales. Chinese architectural heritage styles are a result of growing interest in employing Deep Learning (DL) algorithms and digital data for these kinds of analysis and identification. By preprocessing the data with grayscale image approaches, it becomes easier to extract features using Histogram of Oriented Gradient (HOG) descriptors to capture textural and structural attributes. Following that, the architectural styles are grouped using a new identification model that combines Avian Swarm Optimized K-Nearest Neighbors (ASO-KNN), an improvement over the standard KNN method that incorporates ASO behavior. The efficiency and accuracy of data categorization are increased by this hybrid approach, which maximizes KNN selections. The goal of the study is to properly categorize and describe traditional styles of architecture depending on their distinctive attributes and qualities. The proposed ASO-KNN method outperforms then the existing models AlexNet, DenseNet, and ResNet with the parameters of (89.25%) accuracy, (93.36%) F1-score, (91.59%) recall, and (98.79%) precision, the suggested methodology better than the state-of-the-art methods. These findings support the method's effectiveness and set the stage for further developments in automated architectural style recognition.

Povzetek: Predlagani algoritem ASO-KNN dosega visoko kvaliteto pri prepoznavanju kitajskih arhitekturnih slogov s kombinacijo HOG značilk, DNN in optimiziranega KNN modela, navdihnjenega z vedenjem ptic.

1 Introduction

Human civilization is incomplete without its architectural heritage, which carries the memories of its cities and its historical activities. Beginning with the Renaissance, systemic preservation of architectural legacy was initiated [1]. Buildings and other structures that are prized for their architectural, historical, cultural, or aesthetic significance are referred to as having left a legacy. A society's historical progression, cultural makeupand architectural accomplishments are collectively represented by a diverse array of man-made structures, ranging from imposing landmarks and sacred structures to everyday residences and utilitarian infrastructures.In the setting of the circular economy, information about potential clients can help organize a system for material restoration and maintenance, collection and reuse, as well as the creation of innovative materials that are compatible [2], with the bright circumstances and obligations. Numerous studies have been conducted that offer methods for documenting and identifying buildings at a global scale about the typological research on architecture that guides the identification of structures. Creating sophisticated architectural style information is essential for directing the development of new global architectural styles, revitalizing and changing existing communities and managing urban style. Control criteria for architectural styles, resources found in landscape gardens, cultural sitesand other scope-related elements are already being implemented in several cities. It does not entail unifying all urban buildings into a single style [3]. In cities, this encourages aesthetic coherence. Consequently, regionalism, development and continuity define an urban architectural style. Advancements in DL have enabled machines to forecast various elements of constructed environments [4]. Putting places in a rating system to reflect people's perceptions and categorizing architectural types. Aside from DL in itself, greater computational capacity has led to a growing interest in studying constructed environments through images. The objective of this research is to create and assess an automated system that uses ASO-KNNto precisely identify architectural heritage styles.

The remaining paper has been separated as follows. Part 2 includes related works that are organized according to the study's goal. Part 3 explains the proposed method of heritage style identification andpart 4 provides access to the results as well as discussion. Part 5 consists of a conclusion.

2 Related works

To develop the Convolutional Neural Network Attention Retrieval (CNNAR) framework, the DL techniques were employed [5]. Using the parameters learned from the Paris 500K information sets image source network as a guide, the target network was trained using the transfer learning approach to identify the image in question, yielding the classified image in the first stage. The problem was conveyed by introducing an approach that allows a random forest (RF) [6] model, which was trained on a particular dataset, to be successfully generalized to new circumstances. This sentence clarified the subject and verb, and it correctly uses commas to set off the non essential clause. To do this, the greatest characteristics, such as walls, windows, roofs and columns, were found to be appropriate for identifying the classes of interest. DL has been used to classify images of architectural heritage. The Google LeCun Network (GoogLeNet), Residual network (ResNet18) and resnet50 [7] pre-trained CNNwere suggested for use on architectural heritage images from public datasets. Using DarkNet-53 as the important network for the DLalgorithm and integrating the You Only Look Once (YOLOv3) algorithm, they aim to identify timber-crack damages using Weighted Average Hashing (WAH) [8]. To train and evaluate the timber-crack detection model, a sizable dataset of timber cracks was first created. The study offered a DL algorithm-based method for automatically classifying surface defects of timber architectural cultural material. A basic examination into the expansion of an automated immediate remote break recognition organization was appropriate for civilizing traditional areas [9]. They were investigating a system of recommendations for a local area's architectural history, basing the study empirically on Jiangxi, China. A dataset for the legacy of traditional Chinese architecture was created to structure our research and for the recommendation task, a deep hashing retrieval algorithm [10]. Using CNN [11] methods based on picture organization and feature extraction, this paper presented an autonomous multi-category damage identification technique for historic structures. This technique can detect problems such as material loss, erosion, sabotage issues and stone color change. The Jordanian city of "Al-Salt" was chosen for their research. An innovative approach to measuring the form, features, and assessment of regional architectures using ML technology is being developed. The Chinese Ancient Architecture Image dataset (CAAID) was a set of preparation data that must be created first [12], during which a small group of experts has categorized each image with common traits. Central courtyards were the most characteristic aspect of Iran's historical houses. The research aimed to identify and classify the residences as historical buildings using a CNN model [13] based on this feature. Consequently, the trained model achieved approximately 98% accuracy when tested on validation dataset. Artificial intelligence (AI), architecture, and other multidisciplinary research methodologies are being used to examine the well-known masonry-timber architectural legacy of James Jackson Gymnasium in Wuhan. Architectural heritage cracks data and ailments were gathered using 3D laser scanning technology [14]. Crack areas were detected using individual cracks thatwere identified and calculated using a Fully Conventional Network (FCN) model and an overview regarding the category, position and characteristics of cracks was given at the end. Lastly, the reasons behind the cracks were looked at and matching hierarchical restoration techniques were suggested. The methodological approach that was suggested for Scan-to-Building Information Modelling (BIM) [15] Construction form is a popular topic in the realm of design for buildings, reflecting regional designs to some measure. The work presents an original approach for quantifying the features, form, and assessment of regional structures. As a result, our machine learning-based method can be utilized not only as an analytical instrument for extracting aspects of neighbourhood structures, but also as an effective technique for evaluating architectural forms during the city's regeneration processes [16] as its foundation. Results suggest that interpretation can help people understand and acknowledge the cultural relevance of architectural history. An understanding of the relationship between value in a knowledge domain and morphological features was essential for building analysis in the architecture domain. Their formal complexity was based upon connections and inferences between shapes, as per their spatial and functional hierarchical [17] framework. Many cultural heritage items that were located far away in space but have similar qualities (typologies, styles, compositional norms) were used with digital technologies, which encourage the development of novel scientific frameworks. Virtual reality (VR) and augmented reality (AR) [18], two recent advancements in experience technology, have made it easier to experience architectural heritage in a simulated environment. Fascination user experiences were certain to be constrained even with the advancement of familiaritystrategy if the number and excellence of material were not adequately provided. 3D digitization used actuality capture methods for built heritage explanation and structure investigation. 3D CNN [19] was used for classification during this process. A 3D CNN for determining a building's architectural essentials and analyzing the stylistic effects on those elements was provided by the workflow that is being described. Table 1 represent the comparative related studies.

Table 1: Comparative related work

Ref	**Year**	**Objective**	**method**	**Result**
[5]	2020	With an emphasis on generalizing to novel scenarios, attempts to solve the difficulty of utilizing a single machine learning model to analyze huge and diverse structural information in the context of historic preservation.	Using a random forests model educated on a specific set of data, the study determines important characteristics necessary for categorizing design aspects. Random Sample Consensus (RANSAC)	Precision 0.94, Recall 0.93 F1 score 0.93
[6]	2020	The investigation aims to improve the administration and evaluation of photographs related to cultural property by effectively classifying these photos using deep learning methods.	Already trained convolutional neural networks (CNN) are used. To increase efficiency and better data management and search, the study classifies cultural heritage photos using pre-trained GoogLeNet, ResNet18, and ResNet50.	Accuracy of "87.91", "95.47" and "95.57"
[7]	2020	To enable prompt repairs, the project intends to provide an automated technique that is both precise and effective for identifying timber-crack deterioration in wooden heritage of architecture.	Using DarkNet-53 as a foundational network, the study uses the YOLOv3 method. A sizable timber-crack sample is used to develop and assess the model using deep learning.	Precision 0.85317, precision 0.932, recall 0.8784, and F1-measure 0.9044
[8]	2023	To develop a real-time imperfections classification method for timber heritage of architecture using deep learning.	Used Grad-CAM to visualize the results while comparing four deep learning algorithms using 4,000 photos.	Accuracy 94.0% to 96.50% destruction recognition rate was attained.
[10]	2022	Using CNNs to develop a robotic deterioration detection method for historic buildings that can recognize problems like weathering and substance loss.	The CNN method has shown to be a dependable and efficient tool for maintaining old masonry structures.	accuracy of 95%
[12]	2022	Using CNNs, traditional residences in Yazd, Iran, will be distinguished from non-historical structures by their center gardens.	Used satellite photos to apply CNN. identified ancient gardens with success, demonstrating a novel application of deep computing to Iranian architectural.	It contain accuracy 98%

The suggested ASO-KNN improves the rate of classification, reduces computation, and optimizes choosing features more effectively than existing methods like AlexNet, DenseNet, and ResNet. By leveraging avian swarm characteristics to avoid local minima, ASO-KNN improves convergence speed and improves the identification of architectural styles. Furthermore, in comparison to deeper designs, its compact structure reduces computing expenses and excessive fitting.

3 Methodology

This part investigates the identification of architectural heritage styles using AI techniques. The purpose of ASO-KNN is to develop an efficient AI model to identify heritage styles. First, the data was collectedand then the data was pre-processed using Gray-scale. HOG was utilized to extract features from the preprocessed data. Figure 1 shows the proposed flow for the methodology.

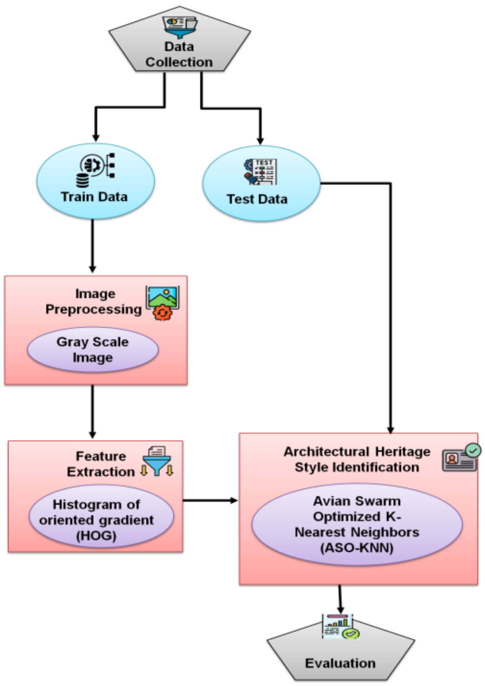

Figure 1: Proposed flow

3.1 Dataset

Over China's lengthy history, numerous unique instances of ancient construction have survived as people have adapted to the local natural environment. Those groups of buildings with certain scales eventually give rise to a specific architectural style that reflects the history and culture of the area. To identify architectural styles that are typical of the Chinese architectural heritage style: the Min, Chuan, Jin and Jing styles. Altogether, around 1200 images were acquired, with roughly 300 images for every category. Splitting the data into training (70%) and testing (30%) ensures a robust evaluation of the model's performance. Figure 2 shows the heritage styles of Chinese architecture.

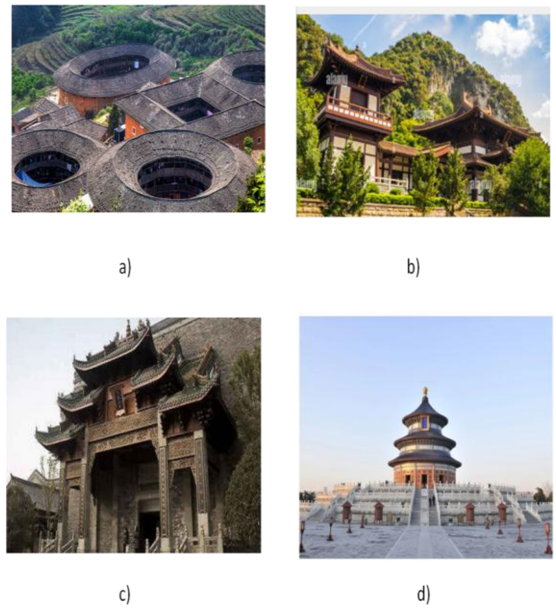

Figure 2: Architectural heritage styles

3.2 Image preprocessing using grayscale image

The image must be resized and noise removed to grayscale. An image can be resized by applying the enlarge function on it and passing it a two-integer triple element that contains the image's current width and height. The method produces an additional picture with the altered dimensions rather than altering the existing image. To convert the image to grayscale in Python, use the conversion Equation (1).

$$imgGray = 0.2989 * Red + 0.5870 * Green + 0.1140 * Blue \quad (1)$$

Using the grayscale method to resize and normalize the images too easily performs and focuses more on intensity values.

3.3 Feature extraction using histogram of oriented gradient (HOG)

After preprocessing, feature extraction is performed using HOG (Histogram of Oriented Gradients). By examining the pattern of gradient directions in specific image regions, the HOG technique is highly effective in identifying the form and structure of details in buildings. Because of their Scale-Invariant Feature Transform, (SIFT) and Speeded-Up Robust Features (SURF) require more computing power than HOG, which is economically economical and successfully highlights the borders and outlines that are essential for differentiating architectural aspects. This efficiency ensures greater speed and precision in feature extraction, which is especially useful when processing big datasets of construction image. This method aims to use a collection of local histograms to characterize an image. The gradient orientation occurrences in specific areas of an image are represented by these histograms. A directed shift in pixel intensity along thew and z axes is known as an image gradient. Equation (2) describes a gradient matrix of a single pixel at points$s(\mathrm{w},\mathrm{z})$.

$$\nabla \mathrm{e}(\mathrm{w},\mathrm{z}) = \begin{bmatrix} h_w \\ h_z \end{bmatrix} = \begin{bmatrix} \frac{\partial e}{\partial w} \\ \frac{\partial e}{\partial z} \end{bmatrix} = \begin{bmatrix} e(w+1,z) - e(w-1,z) \\ e(w,z+1) - e(w,z-1) \end{bmatrix} \quad (2)$$

Where $\mathrm{e}(\mathrm{w},\mathrm{z})$ and $h_w h_z$ are the gradients in the (w) and (z) directions, respectively and(w,z) represents the intensity of the pixels at the locations $(w)$and (z). The gradient's phase, $(\mathrm{w},\mathrm{z})$and magnitude, $N(w,z)$, can then be determined using the following equations (3) and (4).

$$N(w,z) = \sqrt{{h_w}^2 + {h_z}^2} \quad (3)$$

$$\theta(w,z) = arctan\frac{h_z}{h_w} \quad (4)$$

Where the gradients in the$(w)$and(z) directions are$\theta(w,z)$, respectively.

A $50\ x\ 50$-pixel cell size was chosen for this investigation. Using a 50×50-pixel cell yielded a total of five cells arranged in the direction of the horizontal and four in the vertical direction because the final result is 250×200 pixels in size.

$$e = \frac{u}{\sqrt{||u||^2 + f^2}} \quad (5)$$

After obtaining the gradient histogram, each image was subjected to a block normalization procedure using a wedge size of 2 × 2 cells. To get rid of any possible impact from lighting differences, normalization was required. Concentrating block 97 resulted in a vector with dimensions of 20 × 1, as a 2 × 2 block comprised four histograms, each with five bins. Where u is the vector containing all the histograms in a block, f is the vector norm, $\left||u|\right|$ is the normalization factor and $e$is a modest regularization constant. Figure 3displays the HOG feature extraction from the image.

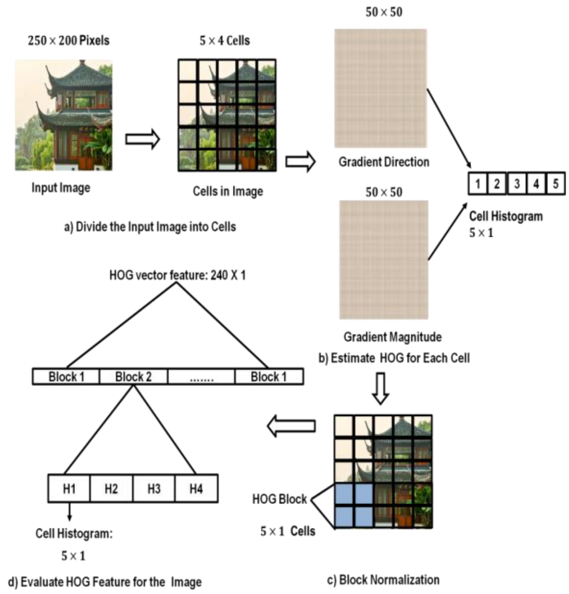

Figure 3: HOG feature extraction

3.4 Identification of heritage style using avian swarm optimized k-nearest neighbour (ASO-KNN)

The suggested method improves efficiency and accuracy in the identification of architectural heritage styles by combining ASO with KNN optimization. This technique uses sophisticated algorithmic synergy to identify historical styles effectively. To improve the process of architectural style categorization, the integrates the advantages of Avian Swarm Optimization (ASO) with the K-Nearest Neighbour (KNN) technique. ASO uses a flexible and adaptable search strategy to optimize KNN the hyper parameters such as the quantity of other residents and distance metrics, in order to mimic the foraging activities of birds.

3.4.1 Improved K nearest neighbour (KNN)

One identification strategy that consistently performs well across a large dataset is the K-nearest neighbour method. It classifies data by calculating the shortest distance between every location in the training set and the remaining data. Due to its reliance on the closeness of currently available training data, the improved KNN algorithm offers greater flexibility. The Euclidean distance formulas were utilized by the improved KNN algorithm to define the distance between object testing and training to accomplish its purpose. Improved KNN depends on the separation between the training sample and the query instance.

The Euclidean distance, which is shown in equation (6), is typically used to compute near or far distances.

$$c(w_j, w_i) = \sqrt{\sum_{q-1}^{m}(b_q(w_j) - b_q(w_i))^2} \quad (6)$$

Equation (7) shows the training data for attribute 1.

$$W_1 = (W_{11,} W_{12,\dots} W_{1\,m}) \quad (7)$$

Equation (8) shows the training data for attribute 2.

$$W_2 = (W_{21,} W_{22,} \cdots, W_{2\,m}) \quad (8)$$

To determine the Euclidean distance, use Equation (9).

$$c(W_1, W_2) = \sqrt{\sum_q^m (b_q(W_1) - b_q(w_{12}))^2} \quad (9)$$

3.4.2 Avian swarm optimization (ASO)

After identification of heritage style using KNN, the identification was refined using ASO. An optimization technique ASO was inspired by bird social behaviour. While searching for food, the sparrow population's social interactions and division of work are simulated by the algorithm. Each bird's flight position serves as a potential solution. Birds that look for food in scattered flight not only preserve population variety but also successfully evade a local ideal alternative. These five strategiesare derived from the searching habits of birds in the wild, which are identified by their social interactions.

Strategy 1: To prevent crowding, birds maintain space from their neighbors.

Strategy 2: Birds change their course to align with their neighbor's average direction.

Strategy 3: To stay together, birds tend to align themselves with their neighbors'average positions.

Strategy 4: Places that have high fitness values (well-designed solutions) draw birds.

Strategy 5: Birds steer clear of places with poor solutions, or low fitness scores.

Birds' social activity comprises both alert behavior and foraging behavior for a larger survival advantage.

3.4.2.1 Foraging behaviour

The arbitrary decision-making procedure of birds is grounded in Strategy 1. Birds feed when the random number between 0 and 1 produced by equal chance is larger than the constant O; otherwise, they stay alert.

Every bird search for its objective based on its individual flying experiences as well as group experiences, in compliance with strategy 2. Consequently, the positionw_ (j, i) ^ (s+1) is provided below at times + 1 are given in Equation (10).

$$w_{j,i}^{s+1} = w_{j,i}^{s} + D * rand(0,1) * (o_{ji} - w_{j,i}^{s}) + T * rand(0,1) * (h_i - w_{j,i}^{s}) \quad (10)$$

Every bird search for its objective based on its individual flying experiences as well as group experiences, in compliance with strategy 2. Consequently, the positionw_ (j, i) ^ (s+1) is provided below at times + 1 are given in Equation (10).

Birds begin to forage if the chance number (0,1) is smaller than a constant ϵ (0,1); otherwise, they stay vigilant.

3.4.2.2 Alert behaviour

The alert behaviour is further explained below Equations (11, 12 and 13) in compliance with strategy 3. Let$k$ be a positive integer ranging from 1 toM,, where $k \neq I$. The variables $a_1$and $a_2$belong to the interval $[0, 2]$. $oFit_j$ Represents the optimal fitness value of the i^{th} bird, while $sumFit_j$denotes the sum of the optimal fitness values of the entire colony. To prevent $sumFit_j$from being zero, a small constant is introduced. Additionally, $mean_j$is the average fitness value of the i^{th}bird.

$$w_{j,i}^{s=1} = w_{j,i}^{s} + B_1 * rand(0,1) * (mean_i - w_{j,i}^{s}) + B_2 * rand(-1,1) * (o_{l,i} - w_{j,i}^{s}) \quad (11)$$

$$B_1 = b_1 * \exp\left(-\frac{oFit_j}{sumFit_{j+F}} M\right), \quad (12)$$

$$B_2 = b_2 * \exp\left(\frac{oFit_j - oFit_l}{|oFit_j - oFit_l| + \varepsilon} * \frac{M * oFit_l}{sumFit_j + \varepsilon}\right) \quad (13)$$

3.4.2.3 Flight behaviour

Accordingly, per strategy 4, birds migrate to different places regularly to escape being chased or in search of food. Migration as a process is configured accordingly. They will eat once more when they get to their new location.

Flying habit is explained in Equation (14) and (15).

$$w_{j,i}^{s+1} = w_{j,i}^{s} + randm(0,1) * w_{j,i}^{s} \quad (14)$$

$$w_{j,i}^{s+1} = w_{j,i}^{s} + rand(0,1) * (w_{l,i}^{s} - w_{j,i}^{s}) * EK \quad (15)$$

Where; (ϵ $[0, 2]$) represents the time intervals separating birds flying to a location to search for food and $(0, 1)$ is a typical Gaussian random number. The proposed Avian Swarm Optimized K-Nearest Neighbour (ASO-KNN) method was used to identify the architectural heritage style such as a) Min, b) Chuan, c) Jin, d) Jing.

4 Result

On a Windows 11 OS, weused the Python programming language to implement suggested techniques. This study suggests an autonomous identification of architectural heritage style based on ASO-KNN. Implementation of an architectural heritage style identification exercise using a collection of images that includes several types of historical buildings.

4.1 Confusion matrix

It is a grid that explains the differences between anticipated and actual class labels to display the proposed ASO-KNN model performance. It has measures that help assess model accuracy and spot misidentifications. Figure 4 shows a confusion matrix for identifying architectural heritage styles with a total of 860 instances. Use the same four styles: Min, Chuan, Jin and Jing. The confusion matrix illustrates a situation in which the suggested model ASO-KNN performs at identifying Chuan compared to the Min architecture.

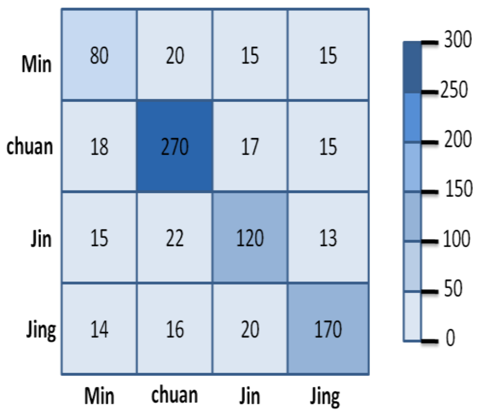

Figure 4: Confusion matrix

4.2 Comparative analysis

Comparative analysis based on metrics such as F1 score, recall, accuracy and precision can be utilized to compare existing methods to identify architectural heritage styles. Table 2 depicts performance analysis of the proposed ASO-KNN method and existing methods such as the Alex Krizhevsky Network (AlexNet) [20], Densely Connected Convolutional Network (DenseNet) [20] and Residual Network (ResNet) [20].

Table 2: Outcomes of proposed and existing method

Methods	**Precision (%)**	**Recall (%)**	**Accuracy (%)**	**F1 score (%)**
Alexnet [20]	77.21	57.53	57.53	63.56
Densenet [20]	97.08	82.92	82.92	88.56
Resnet [20]	94.80	73.02	73.02	81.41
ASO-KNN [Proposed]	**98.79**	**91.59**	**89.25**	**93.36**

Accuracy: The proportion of accurate forecasts among all of a model's forecasts is known as accuracy. Precise placement and measurement are crucial for the successful identification of architectural heritage style. The results of accuracy for the suggested and current approaches are shown in Figure 5. Compared to the AlexNet (57.53%), DenseNet (82.92%) and ResNet (73.02%) approaches, the recommended (ASO-KNN) method yielded a superior accuracy of 89.25%.

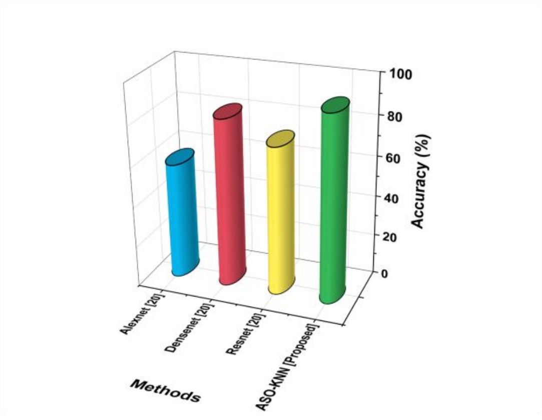

Figure 5: Outcomes of Accuracy

Precision: Precision can be defined as the proportion of accurately anticipated instances that were positive to all cases that the algorithm projected as positive. Figure 6 shows the comparative outcomes of precision. The suggestedASO-KNN approach produced a greater98.79% precision value whereas the AlexNet acquired 77.21%, the DenseNet obtained 97.08% and the ResNet displayed 94.80%.

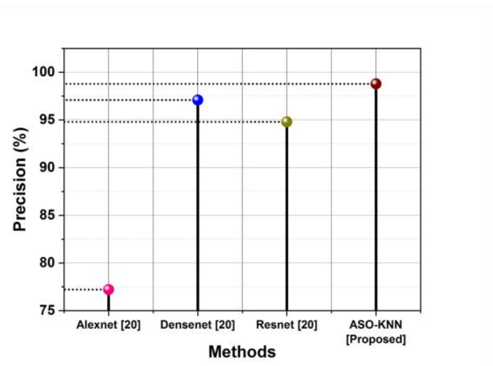

Figure 6: Outcomes of precision

F-1 Score: The F1 value is a metric that is commonly used in tasks involving binary identification to assess test performance. It is calculated using the harmonic means of recall and precision. Figure 7 shows the outcomes of precision values of proposed and existing methods. In contrast to other current approaches like AlexNet (63.56%), DenseNet (88.56%) and ResNet (81.41%), the suggested (ASO-KNN) approach produced better outcomes with 93.36% of F1-score.

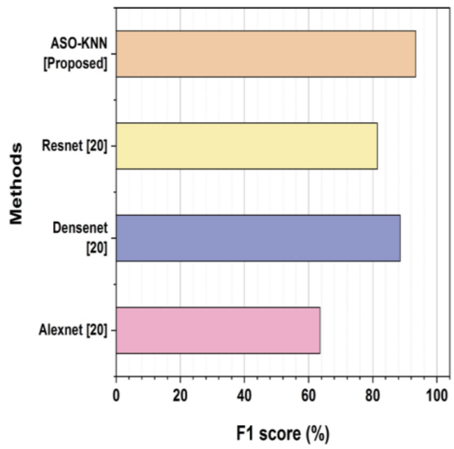

Figure 7: Evaluation of the F1 score

Recall: In the context of identifying architectural heritage style, recall refers to a detection system's capacity to accurately identify relevant examples of heritage style from among all of the actual instances that are present. Figure 8 shows the recall of heritage style identification. Compared to the AlexNet (57.53%), DenseNet (82.92%) and ResNet (73.02%) approaches, the recommended (ASO-KNN) method yielded anadvancedrecall of 91.59%.

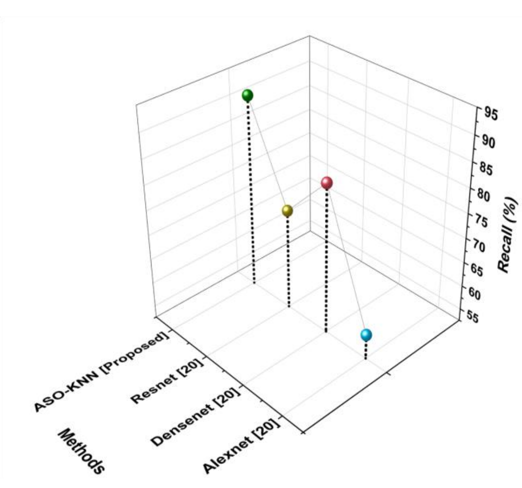

Figure 8: Comparative Outcomes of Recall

This hybrid strategy improves KNN's ability to identifying tiny distinctions between architectural styles by utilizing ASO's capacity to search the parameter space effectively. Compared to more conventional methods like weighted KNN or K-means clustering, this unique approach offers more accuracy and flexibility in heritage style detection by combining the sophisticated optimization of ASO with the basic categorization of KNN. ASO enhances KNN by optimizing the distance calculations, leading to better accuracy in identifying heritage styles. Cross-validation helps ensure the model performs well on different data subsets, reducing the risk of overfitting and making the results more reliable.

5 Discussion

The Avian Swarm Optimized K-Nearest Neighbors (ASO-KNN) model has various advantages for identifying architectural heritage styles, including adaptation to smaller datasets and efficiency in feature selection using avian swarm-inspired optimization approaches. This produces a model that is fewer computationally expensive and more comprehensible, making it ideal for scenarios with little information or capabilities. Conversely, cutting-edge models such as AlexNet, DenseNet, and ResNet, while significant, have significant limitations. Despite its revolutionary status, AlexNet's somewhat shallow architecture makes it less effective at managing complicated data. DenseNet, which addresses the issue of disappearing gradients with dense interactions, can be physically costly and susceptible to overlapping in extremely deep the internet. ResNet, have high computing requirements and difficulty, necessitating considerable time and money for development and inference. Thus, while ASO-KNN is a more environmentally friendly and uncomplicated strategy, sophisticated algorithms may have greater expenses and complications. Potential enhancements to the robustness of historical architectural style verification could involve integrating ASO-KNN with sophisticated neural networks for increased precision and effectiveness, using domain-specific extraction of features and communicate learning to adjust to different styles, and applying ensemble approaches to improve simulation dependability and speculation.

6 Conclusion

The study shows that cutting-edge Deep Learning (DL) algorithms and digital data may be used to efficiently assess and identify the distinctive architectural elements and construction methods characteristic of Chinese architectural heritage styles. The work improves the identification of architectural types by preprocessing data using grayscale picture techniques and capturing textural and structural aspects using Histogram of Oriented Gradient (HOG) descriptors. Accuracy and efficiency of data classification are greatly enhanced by the introduction of a hybrid model that leverages ASO behavior to combine Avian swarm-optimized K-Nearest Neighbors (ASO-

KNN) with regular KNN. The excellent performance measures achieved by the suggested methodology, which outperforms current state-of-the-art methods, include 89.25% accuracy, 93.36% F1-score, 91.59% recall, and 98.79% precision. These outcomes validate the method's efficacy and open new avenues for automated architectural style identification system development.

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