www.cad-journal.net
Computer-Aided Design AND APPLICATIONS™

Architectural Style Classification Based on Deep Learning

Huiyu Li[1] and Hailong Dong[2]

[1,2] Department of Intelligent Architecture, Zhejiang College of Security Technology, Wenzhou 325016, China, [1]18076136@zjcst.edu.cn, [2]18066134@zjcst.edu.cn

Corresponding author: Huiyu Li, 18076136@zjcst.edu.cn

Abstract. This article analyzes the efficient classification of computer models using different architectural styles. A precise feature application for computer-aided design was constructed by evaluating and classifying CAD data training. A deep learning-based model was used for building model training. The research experiment uses the evaluation model's test dataset classification information during the iterative process. Under strict training indicators, the test dataset showed a high-performance level in classifying architectural styles. In the automatic extraction process of architectural images, the method proposed in this article has a high ability for style transformation in processing architectural style data models. In the process of precise automatic extraction of architectural style, the model has a deeper efficiency in building data. This has high accuracy and application value in the style conversion of image architecture.

Keywords: Deep Learning; Computer-Aided Design; Classification Of Architectural Styles; Convolutional Neural Network; Data Fusion
DOI: https://doi.org/10.14733/cadaps.2025.S1.16-31

1 INTRODUCTION

Image segmentation is a crucial step in image processing. Image segmentation plays an important role in tasks such as 3D reconstruction in the field of architecture. Therefore, it is necessary to propose an efficient color-building image segmentation algorithm. It is difficult for existing segmentation algorithms to perform well in the face of diverse segmentation objects which cannot meet the needs of users. Byun and Sohn [1] regarded the essence of image segmentation as the clustering of pixels as the basis for analysis, combined specific segmentation methods with segmentation objects, and analyzed and studied the K-means algorithm. Classifying pixels solely based on the Euclidean distance between pixel coordinate positions cannot fully describe the distribution characteristics of pixels, which can easily lead to misclassification of pixels. Then, a reasonable number of classifications and representative initial centre points are obtained through the colour histogram of the image. Firstly, through preprocessing, the algorithm converts the clustering objects into pixel blocks, effectively reducing the computational complexity of the algorithm. Due to the utilization of the overall colour distribution characteristics of the image, more reasonable classification numbers and initial centre points are obtained. This algorithm first establishes a colour histogram of the image in the HSI colour space and scans the colour histogram vertically and horizontally to obtain peak points with high density and a certain distance apart. Further, analyze the characteristics of color-building images, use multidimensional feature constraints to calculate the similarity between pixel blocks, avoid misclassification of pixel blocks, and improve image segmentation performance. This algorithm analyzes the characteristics of colour-building images and proposes to separately calculate the similarity of pixel blocks in colour, texture, and spatial position features, and combine the three as the final similarity to partition pixel blocks. The accurate classification of these styles not only offers inspiration for architectural designs but also advances the preservation and continuation of our cultural heritage.

Digital tools not only serve as key supporting elements for complex structures in the architectural design process but also play a decisive role in showcasing and interpreting different architectural styles. The new opportunities brought by digital media not only help architects execute design processes more efficiently and accurately but also allow them to explore and present different architectural styles more flexibly. Although design-based courses have always been the core of architectural education, graphic communication courses, especially those involving digital software, have gradually become important supportive and decisive elements in the design process. At the same time, the school also focuses on cultivating students' ability to use digital tools to express and present different architectural styles. By combining tradition with modernity, hand drawing with numbers, students can use design tools more flexibly on the basis of understanding architectural style, and create architectural works that meet standards and have unique charm. Through digital tools, Ceylan [2] Simulates and showcases various styles, from classical symmetry and stability to modern simplicity and streamlining, and to the unique charm of regional architecture. Furthermore, this classification is pivotal for urban planning and tourism enhancement, bolstering the city's image and cultural influence.

At present, traditional algorithms and convolutional neural networks are used to handle the relationships between images, but existing convolutional neural network models and traditional algorithms extract image features from different perspectives. Esmaeily and Rezaeian [3] proposed a key point extraction method for building images based on a combination of traditional algorithms and convolutional neural networks, addressing the aforementioned issues between building images. They also incorporated attention mechanisms to improve accuracy. Combining the SIFT algorithm with the ORB algorithm to extract different key points and improve matching accuracy. The use of ratio testing algorithms effectively eliminates mismatched points, thereby improving the reliability of matching results. Due to the similarity between different architectural styles and the differences within the same architectural style, there is a lack of labelled architectural categories in the dataset. The use of zero-sample classification technology to classify building images with missing label data has become a topic worthy of research. Due to the uniqueness of architectural style, most feature extraction methods find it difficult to effectively extract key features of architectural style. Multiple emerging buildings retain early architectural elements, and the relationship between semantic labels of different categories is similar, making it difficult to learn classifiers with high fitness. Han et al. [4] studied zero sample architectural image classification based on a dual attention mechanism and weighted graph convolutional network. Firstly, two models, channel attention and spatial attention, are introduced to enhance the representation of specific regions in the image. Among them, the channel attention network learns different channel weights to locate buildings in the image. To effectively locate building elements related to classification tasks in building images, a zero-sample building image classification method based on a dual attention mechanism is proposed. Finally, design a zero sample architectural image classification model embedded in public spaces, align visual and semantic features in subspaces, and achieve classification tasks through nearest neighbour matching. The effectiveness of the method was verified through experiments. Channel spatial attention can focus on important areas related to the task in the image, ignoring unimportant elements. Therefore, in order to effectively extract the main body and its detailed features of buildings and explore the strong correlation of semantic labels between different styles in the absence of building image label data. This algorithm not only considers the geometric shape of the building but also incorporates its stylistic features when generating the final CAD drawings, making the drawings more detailed and accurate. By fine-tuning the model to identify the style features of different architectural elements, such as windows, doors, roof styles, etc., we can further classify the scanned buildings into different styles. In terms of architectural style classification, the model also demonstrates good performance, accurately distinguishing different architectural styles, such as modern, classical, Gothic, etc. Not only did it generate the final computer-aided design (CAD) drawings for landscape architecture, but it also further integrated the analysis of architectural style classification.

In the field of architectural design, 3D CAD technology has also become the focus of research and application, and 3D design is regarded as an inevitable trend for the future development of the architectural field. On the basis of comprehensive analysis and comparison of various architectural styles, Hu [5] utilizes 3D feature modelling and parameterization techniques to establish a 3D architectural feature library of different styles. Just as 3D feature modelling and classification of plastic parts are used in engineering drawing design, architectural style classification also requires the use of 3D CAD technology to capture and express the unique features of various styles. Architectural style is not only a carrier of culture and history but also an important consideration factor in the design process. These feature libraries can contain key elements and features of various styles, from classical Gothic and Baroque to modern minimalism, deconstructionism, and more. This digital model not only showcases the building model itself but also simulates the performance of the building on different projection planes, thereby more realistically and intuitively displaying the orthogonal views of the building design. Designers can more conveniently call upon these features when creating building models, and adjust and optimize them as needed. This novel interpretation method, using digital means to simulate and interpret orthographic views in architectural design, helps designers better understand and express their design intentions. Currently, there have been attempts to integrate CAD technology into architectural style classification. Krner et al. [6] established a computational design and simulation model to analyze the kinematic and dynamic behaviour of abstract biological principles under specific material, manufacturing parameters, constraint conditions, and architectural style characteristics. Firstly, an in-depth analysis was conducted on the characteristics of different architectural styles, such as the symmetry and stability of classical architecture, the simplicity and streamlining of modern architecture, and the unique elements of regional architecture. The folding motion of the demonstrator is promoted through different elastic hinge regions with integrated pneumatic actuators, and the design of these hinge regions also fully considers the characteristics of the architectural style. In the folding mechanism of classical architectural style, we pay more attention to symmetry and stability, so that the entire mechanism presents a classical charm when folded. Through this model, it can simulate various building folding motions based on bionic-compliant mechanisms, and evaluate their performance in different architectural styles. The folding mechanism of modern architectural style adopts a more concise and streamlined hinge design to reflect the lightness and dynamism of modern architecture. This framework not only includes abstract processes of biological principles such as kinematic behaviour, driving mechanisms, and materialization principles but also delves into how to integrate the characteristics of traditional architectural styles into modern architectural dynamic design.

These studies primarily rely on DL models for feature extraction and image classification, yielding impressive results. Nonetheless, further enhancements are needed in model design and optimization.

The aim of this article is to integrate DL models with CAD technology, creating a novel model for classifying architectural styles. This model leverages the rich image data and design elements inherent in CAD data to precisely categorize various architectural styles. Here are its key innovations:

(1) This article uniquely merges CAD technology with DL, harnessing CAD's precise building data to furnish the DL model with detailed and exact features like structure, shape, and material. This integration elevates both the precision and efficiency of architectural style classification, introducing a multi-level feature fusion model.

(2) In developing the DL model, we introduce an original multi-level feature fusion approach. By blending distinct layers of feature information, our model captures the nuanced variations in architectural styles more comprehensively, bolstering classification accuracy and robustness.

(3) To tackle the challenge of limited data in architectural style classification, we employ data augmentation techniques. This generates additional training samples, thereby enhancing the model's generalization capabilities. Furthermore, we refine the DL model's structure and parameters to optimize classification accuracy and efficiency.

The article is structured as follows: The introductory section outlines the research backdrop, significance, and current trends. Next, the theoretical framework elucidates the fundamentals of CAD technology and DL. The third segment delves into model construction, detailing the process and methodologies involved. The fourth part focuses on experimental design and analyzing results, simulating the model, and evaluating its performance. Case studies are explored in the fifth section, examining practical applications. Finally, the sixth section summarizes our findings and outlines potential future research directions.

2 RELATED WORK

The development of modern science is increasingly characterized by complexity and interdisciplinary nature. As barriers between different fields gradually dissipate, unexpected connections and intersections begin to emerge, and these interdisciplinary research fields, which we refer to as "interdisciplinary," are showing enormous potential. When we delve deeper into the commonalities between architectural design and optics, Livshits et al. [7] found that both require consideration of multiple aspects in the design process, including the interaction between light and space, the presentation of visual effects, and the use of materials. In the seemingly completely different fields of architectural design and optics, we have also discovered unexpected commonalities and similarities. This algorithm will be able to simulate and analyze the interaction effect between light and space under different architectural styles, providing a new design tool for architects and optical experts. Through this algorithm, we can predict key indicators such as lighting and shadow effects, visual comfort, and energy efficiency of buildings under different architectural styles. Taking architectural style classification as an example, different architectural styles not only represent different aesthetic pursuits and historical characteristics but also contain their own unique design concepts and technical requirements. This will greatly improve design efficiency, reduce trial and error costs, and provide designers and experts with more creative inspiration. Due to the complexity and diversity of information contained in colour images, as well as the widespread application of image processing techniques, research on colour image segmentation technology has been continuously developing. Makransky and Petersen [8] used the K-means clustering algorithm to cluster image pixels as a basis for unfolding and analyzing the image features selected by existing colour image segmentation algorithms and their advantages and disadvantages. We selected the efficient and easy-to-implement K-means clustering algorithm to cluster image pixels. We are seeking more suitable colour image features and exploring segmentation methods that are more effective and applicable than using a single feature. Subsequently, to address the shortcomings of the K-means algorithm, which requires users to input initial parameters and results in unsatisfactory image segmentation in the field of architecture, a colour histogram based on image HSI colour space was proposed. In order to reduce the amount of data calculated by the algorithm, superpixel segmentation preprocessing is performed on the image, converting clustering operations on individual pixels into clustering operations on pixel blocks.

Nie et al. [9] proposed a multi-dimensional feature calculation method for similarity, which analyzes the features of colour-building images and uses the colour information, texture features, and spatial position features of colour images as feature parameters for pixel-to-pixel similarity calculation. Calculate the similarity of pixel blocks on three different features separately, normalize and add them together to obtain the final similarity, which is used to classify pixel blocks. Obtain segmentation results to overcome the limitation of using only a single feature and achieve more ideal image segmentation results. In certain areas with prominent stylistic features (such as roofs, eaves, etc.), the density of key points may be higher, and these areas will be prioritized for processing. After determining the units, we define the connecting areas of these units as clusters based on the similarity of local regions. These clusters not only contain similar feature points in the image but also reflect the characteristics of architectural style. Virtual reality tools have brought revolutionary changes for engineers to interact and review designs in a global environment, and their application in architectural style classification also has enormous potential. Nysetvold and Salmon [10] conducted a user study aimed at evaluating the navigation and selection tools available on CAD design review platforms in architectural style classification tasks in virtual reality environments. Through appropriate tool design and application, virtual reality provides a promising framework for modern collaborative engineering, especially in terms of architectural style classification. When conducting the task of architectural style classification, the test participants did not concentrate on using a specific set of tools that were considered the most effective. On the contrary, personal preferences and habits dominate tool selection. In this way, users can select the appropriate toolset based on the specific tasks of architectural style classification, thereby improving work efficiency and accuracy. Modularization means that virtual reality systems should have flexible configuration options, allowing users to choose or customize tools and functions according to their own needs.

The importance of protecting historical heritage lies not only in its physical existence, but also in the culture, history, and architectural style it carries. Although traditional drawing and photo recording methods can capture the physical characteristics of architectural heritage, they often overlook the perception and experience of tourists in space. In order to comprehensively record and protect historical heritage, Tai and Sung [11] are committed to developing a method that combines digital photography technology and architectural style classification to capture and record the visual perception experience of architectural spaces. In perception research, participants are required to recall and describe their experiences in different architectural styles and spaces. The results indicate that the most frequently viewed scenes identified through behaviour mapping are often highly correlated with typical spatial layouts and visual elements in specific architectural styles. Based on the viewpoints identified by these two methods, we propose a possible approach to archive architectural spatial perception experiences using digital photography technology. These data still mainly focus on the physical structure of buildings, with insufficient attention paid to architectural style and the visual perception experience it brings. Such archives can not only record the physical characteristics of the building but also capture the perception and experience of tourists in the space, thus more realistically restoring the style of historical heritage. The computational analysis further confirms the visual importance of these locations, that is, they are not only the most frequently viewed by tourists, but also the places where the most spatial information can be observed. Tastan et al. [12] delved into the availability and constraints of two modelling methods for architectural style classification in immersive virtual reality (IVR) environments: handheld user interface (HUI) and direct operation modelling (DM). They also found that the influence of real-time scale features during the modelling process is crucial for modelling different architectural styles. After analyzing the data using qualitative coding methods, we found that different architectural style classifications have a significant impact on the availability and constraints of modelling techniques during the modelling process. However, in modern or minimalist styles that require rapid large-scale modelling, The HUI modelling method provides higher modelling efficiency through its flexible gesture operations and convenient menu interface. The results show that improvements in mobile technology and optimization of modelling interfaces are crucial for improving modelling efficiency and user experience. Especially when dealing with large-scale building scenes, smoother movement operations and a more intuitive interface design can greatly improve the efficiency and accuracy of modelling.

The inheritance and innovation of ancient architectural decoration art play a crucial role in the development of the construction industry. To overcome this challenge, Based on in-depth research on various architectural style classifications, Xin and Daping [13] combined neural networks and image feature processing techniques. This not only affects the accurate presentation of ancient architectural decorative artworks but also limits their in-depth research and application. Through this system model, we are able to graphically express the static construction mode and dynamic construction process of building clusters. These 3D models and simulation scenes not only realistically restore the original appearance of ancient buildings, but also provide detailed classification and presentation based on architectural style classification, providing researchers with rich visual materials and data analysis foundations. This model not only accurately captures the detailed features of ancient architectural decoration art, but also intelligently analyzes and processes according to the classification of architectural styles. The data processing method of traditional ancient architectural decoration art is relatively lagging, which often leads to distortion in the digitalization process. The experimental results show that the system model can effectively reduce distortion and improve the digital effect of ancient architectural decoration art during the digitization process.

Zhang et al. [14] proposed an enhanced architectural scene framework that not only supports architects to analyze and evaluate design schemes in the early stages of design but also incorporates extended analysis of architectural style classification. The development of coastal urban construction zones undoubtedly has profound significance. The architectural style of coastal cities and their degree of harmony with urban space play a crucial role in improving the overall urban landscape and the quality of life of residents. The development and utilization of coastal landscapes not only pursue poetic visual effects but also achieve effective spatial expansion and functional diversification through scientific planning and reasonable layout. Traditional architectural styles, such as the landscaping techniques of Chinese classical gardens, can be combined with modern design elements to create urban spaces that have both traditional charm and modernity. Zhou [15] has improved the comfort and livability of the building by designing a reasonable ventilation and lighting system. From the perspective of architectural style classification, the architectural design of coastal cities should fully consider their regional characteristics and cultural background. As one of human instincts, hydrophilicity makes the integration of architectural design and marine landscape in coastal cities particularly important. In terms of spatial design philosophy, coastal cities should pay more attention to the openness and fluidity of space. Create an open, transparent, and layered urban space through reasonable spatial layout and landscape design.

3 THEORETICAL BASIS

CAD technology leverages computers to assist designers in their creative processes. CNN's forte lies in its ability to efficiently identify local image features, integrating and transforming them for profound image comprehension. Furthermore, CNN demonstrates remarkable resilience and adaptability, accommodating images of varying sizes and shapes.

Architectural style refers to the comprehensive characteristics of buildings in form, structure, material, and colour. It reflects the aesthetic concept and value orientation in different periods, regions, and cultural backgrounds. The classification of architectural styles can be carried out according to different standards, such as geographical division, time division, material division, etc. (as shown in Table 1).

Classification criteria	Style type	Style Description
Geographical division	1. China's traditional style	Architectural styles that integrate elements of Chinese history and culture, such as palaces, temples, gardens, etc.
	2. European classical style	Including various architectural styles from European historical periods such as ancient Rome, ancient Greece, and the Renaissance.
	3. Islamic style	Commonly found in the Middle East, it is characterized by pointed arches, horseshoe-shaped windows, etc.
	4. Indian style	Architectural styles in India and South Asia, such as the Taj Mahal.
	5. Mediterranean style	Commonly found along the Mediterranean coast, it is characterized by white walls, red roofs, etc.
Time division	1. Classical style	Emphasis on symmetry, proportion and geometric shape, such as ancient Greek and Roman style.

	2. Medieval style	Including Gothic and Romanesque, featuring pointed arches and flying buttresses.
	3. Modernist style	The architectural style in the early 20th century emphasized functionality, simplicity and the use of new materials.
	4. Postmodernist style	Criticism and transcendence of modernism emphasize individuality and pluralism.
	5. Contemporary style	Contemporary popular architectural styles include minimalism and high-tech styles.
Material division	1. Brick and stone style	The architectural style mainly uses masonry materials, such as medieval castles.
	2. Wooden style	Architectural styles mainly use wood, as in traditional Japanese architecture.
	3. Steel and Glass Style	Architectural styles use steel and glass as the main materials, such as modern skyscrapers.
	4. Concrete style	Architectural styles mainly use concrete materials, such as modernist architecture.
	5. Composite material style	An architectural style that uses a variety of materials to meet specific design needs.

Table 1: Classification of architectural styles.

The classification of architectural styles faces some challenges and difficulties, as shown in Table 2.

Challenges and difficulties	*Simplified description*
Style diversity	It is difficult to cover all architectural styles with a unified standard.
Multiple influencing factors	Multiple factors such as history, culture, and geography influence style classification.
Subjective issues	Artificial judgment has subjectivity and uncertainty.
Data acquisition and processing	Obtaining and processing high-quality building image data is difficult.
Technical challenges	DL technology needs to be improved in terms of style feature extraction and classification.
Real-time interaction requirements	Need a quick response and intuitive and user-friendly interface.
Cross-domain integration	It is necessary to integrate knowledge from multiple fields such as architectural history and culture.

Table 2: Challenges and difficulties of architectural style classification.

As a new method, DL technology has a strong ability for feature extraction and classification, which provides new ideas and methods for architectural style classification. By training the DL model to identify and understand architectural features in CAD data, automatic classification and analysis of architectural styles can be realized. This will help to promote the development and application of architectural style classification.

4 CONSTRUCTION OF ARCHITECTURAL STYLE CLASSIFICATION MODEL

Depending on specific task demands, we fine-tune the model's structure by modifying the network layers, convolution kernel dimensions, and counts. The refined CNN structure is depicted in Figure 1.

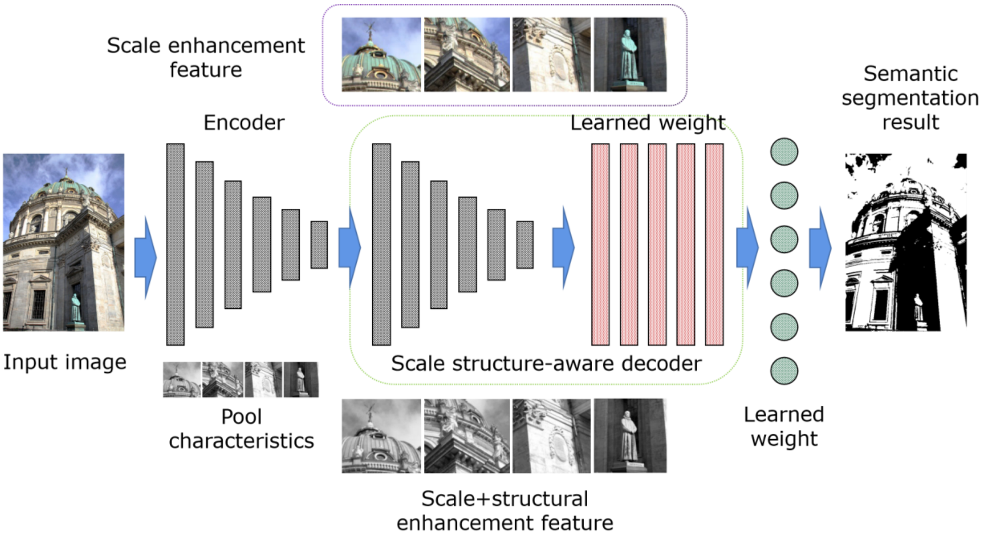

Figure 1: Architecture diagram of convolutional neural network.

In the DL model, feature extraction and classifier are two important components. The feature extraction part is responsible for extracting useful feature information from the input data for subsequent classifiers to classify. In the task of architectural style classification, DL models such as CNN can be used to extract image features and design element features from CAD data. If the expected output vector of neurons in the output layer is:

$$T_s = \left[T_1, T_2, T_3, \ldots, T_{N3}\right] \tag{1}$$

The actual output vector is:

$$O_s = \left[O_1, O_2, O_3, \ldots, O_{N3}\right] \tag{2}$$

The correction error of each neuron in the output layer is:

$$d_s^k = \ t_s^k - o_s^k \ \ o_s^k \ \ 1 - o_s^k \qquad s = 1, 2, 3, \ldots, N_3 \tag{3}$$

Where d_s^k is the correction error of each neuron in the output layer?

The classifier part classifies the input data according to the extracted feature information. When designing the classifier, this article chooses the commonly used classifier algorithm-support vector machine and adjusts and optimizes it according to the needs of specific tasks.

Suppose there is an unknown hyperplane (namely function f), which can fit all the training sample data without error. Moreover, we require that the distance from the sample point to this hyperplane is less than or equal to a constant ε , which is a constraint condition of the model. Because the real hyperplane equation is unknown, we can only use the collected sample data to fit these data by linear regression method so as to get an approximate linear function:

$$f \ x \ = w \cdot x + b \tag{4}$$

It can be obtained that:

$$y_i - \ w \cdot x_i + b \ \le \varepsilon$$
$$w \cdot x_i + b \ - y_i \le \varepsilon, \quad i = 1,2,\cdots,n \tag{5}$$

The SVM classification algorithm converts the challenge of locating the hyperplane solution into a solvable task:

$$\begin{cases} \quad \min \left\| w \right\|^2 / 2 \\ s.t. \quad y_i \ \ w \cdot x + b \ \ge 1 \end{cases} \tag{6}$$

The corresponding prediction function is:

$$f \ x \ = \operatorname{sgn}\left(\sum_{i=1}^{n} a_i y_i \left\langle x_i \cdot x \right\rangle + b \right) \tag{7}$$

Among them, w is the normal vector, b the displacement term, y_i and a label (category), x_i is the input vector. By maximizing the objective function and satisfying its constraints, the values of w and b can be obtained. $y_i \left\langle x_i \cdot x \right\rangle$ is a kernel function, which can map the input space to the high-dimensional feature space and transform the original nonlinear problem into a linear problem.

Integrating CAD data with the DL model is one of the key steps in realizing architectural style classification. When selecting a fusion method, specific task demands and data characteristics must be carefully considered. If CAD data incorporates extensive visual information (e.g., building aesthetics and textures), converting it to an image format for input is advisable. Conversely, if CAD data primarily focuses on design elements and distinct features (such as building dimensions and structures), this data can be directly utilized as DL model input.

During DL model training, selecting an appropriate loss function and optimization algorithm is essential. The loss function quantifies the discrepancy between the model's predictions and actual results. Popular loss functions encompass cross-entropy and mean squared error, among others. For the multi-classification challenge of architectural style, this article opts for the ReLU function, defined as follows:

$$\varnothing \ x \ = \max \ x, 0 \tag{8}$$

When the input signal value is less than 0, the ReLU activation function consistently outputs 0. Conversely, for input signal values greater than or equal to 0, the ReLU function's output mirrors the input signal, preserving a linear correlation.

The optimization algorithm fine-tunes the model's parameters to minimize the loss function. Standard optimization algorithms encompass gradient descent, momentum, and Adam, among others. This article opts for the momentum algorithm, which mimics physics' momentum principle to expedite the learning rate during optimization. The momentum algorithm's updating formula is articulated as follows:

$$\upsilon_t = \mu \cdot \upsilon_{t-1} - \eta \cdot \nabla_\theta J \ \theta \tag{9}$$

$$\theta_{t+1} = \theta_t + \upsilon_t \tag{10}$$

Among them:

υ_t υ_t is the speed at the time step N_{new} t, which is the core variable in the momentum algorithm?

N_{new} is the coefficient of momentum term, which usually takes the value between 0 and 1, and it determines the degree of influence of the previous speed on the current speed.

η is the learning rate, which determines the step size of each update step.

$\nabla_\theta J \ \theta$ is the gradient of the loss function $J \ \theta$ with respect to the model parameter θ.

θ_t is the model parameter at the time step t.

During the training of DL models, it is crucial to fine-tune the model's hyperparameters. Hyperparameters, which include elements like learning rate, batch size, and iteration times, must be preset before commencing the training process. The chosen values of these hyperparameters significantly impact the training outcomes and the model's ultimate performance. When adjusting the super parameters, this article adopts some commonly used strategies, such as grid search, random search, Bayesian optimization and so on. These strategies can help us quickly find a set of suitable parameters so that the model can achieve better results in the training process.

5 EXPERIMENTAL DESIGN AND RESULT ANALYSIS

5.1 Construction of Experimental Environment

In order to carry out the experiment, it is necessary to build a suitable experimental environment first. In terms of hardware, this article chooses a computer with a high-performance processor, large-capacity memory, and high-speed storage equipment to ensure the training and reasoning speed of the DL model. In terms of software, we installed the operating system (Windows) suitable for DL tasks and installed the DL framework (PyTorch) and related dependency libraries. These software tools provide us with all the functions needed to build, train and assess the DL model.

In addition to the basic software and hardware environment, this article also uses some specific experimental tools and platforms to assist the experiment. For example, this article uses OpenCV, a data preprocessing tool, to transform and enhance the format of CAD data. TensorBoard, a visual tool, is employed to exhibit the training process and outcomes of the model, whereas the model's performance is evaluated using the assessment tool (specifically, the assessment function) from the Sklearn library.

5.2 Experimental Process and Result Analysis

Prior to conducting the experiment, this article segments the dataset into three distinct components: training, validation, and test sets. The training set serves to train the DL model, while the validation set aids in evaluating the model's performance and fine-tuning the hyperparameters throughout the training phase. Lastly, the test set assesses the model's generalization capability post-training. During the experimental phase, the article outlines the hyperparameters and training approach for the model. Through comparative experiments, the impact of various configurations on model performance is examined, with the findings presented in Figures 2 and 3.

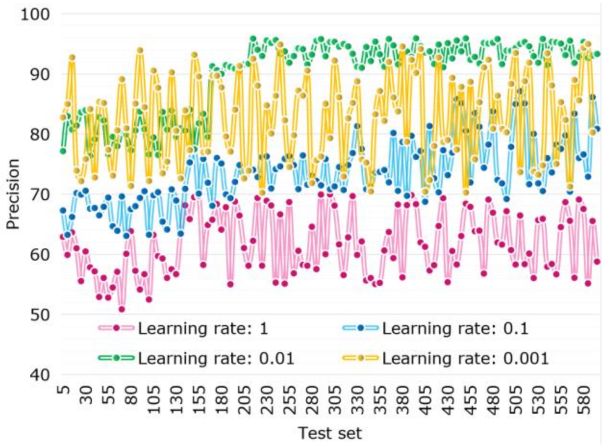

Figure 2: Learning rate setting.

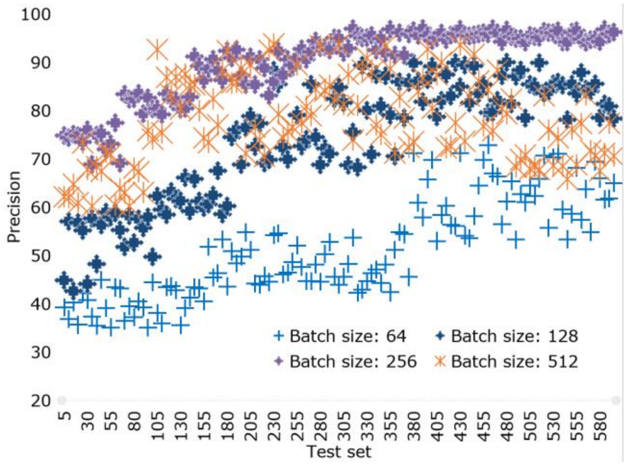

Figure 3: Batch size setting.

Drawing from the experimental results depicted in Figures 2 and 3, this article has established a learning rate of 0.01 and a batch size of 256. During the model training phase, the DL model is trained using the designated training set, and its performance is consistently tracked through the validation set. Upon completion of training, the model's proficiency is tested using the test set, and its performance metrics are documented. This article evaluates the model's performance based on various indicators, including classification accuracy, MAE, and algorithm execution time. To authenticate the efficacy of our proposed approach, a comparative experiment has been devised. In the comparative experiment, this section selects several representative benchmark methods (support vector machine (SVM) classification algorithm, model based on RNN architecture) as the comparison objects. These methods are trained and tested in the same experimental environment and data set as the proposed methods, and their performance is compared. The results are shown in Figures 4, 5 and 6.

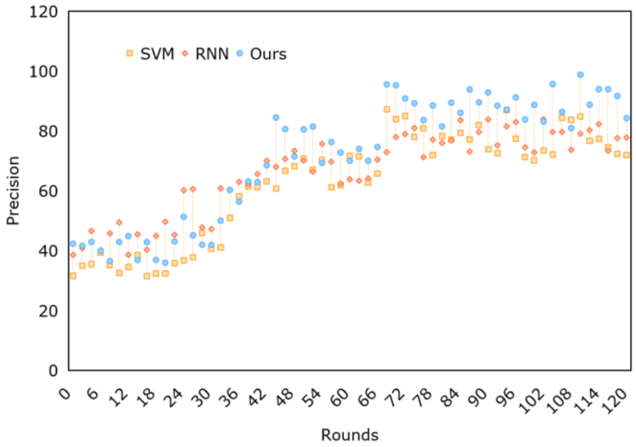

Figure 4: Accuracy comparison of three methods.

Figure 4 shows the comparison results of SVM, RNN, and our DL method in terms of classification accuracy. It can be clearly seen from the graph that the DL method proposed in this article performs the best in terms of accuracy, followed by the RNN method, and the SVM method has the lowest accuracy. The significant advantage of the DL method in classification accuracy is mainly due to its powerful feature extraction and learning capabilities. Through the multi-layer structure of deep neural networks, DL models can automatically extract useful features from raw data and learn the relationship between these features and target variables. This end-to-end learning approach enables DL models to more accurately capture the inherent patterns and patterns of data, thereby achieving better performance in classification tasks. This result fully demonstrates that the DL method proposed in this paper has higher classification performance and stronger generalization ability when dealing with specific tasks.

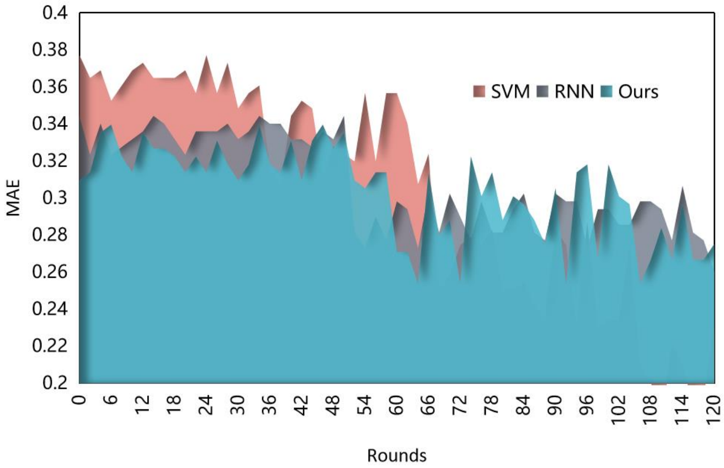

Figure 5: MAE comparison of three methods.

Figure 5 visually illustrates the comparison results of these three methods on the performance metric of mean absolute error (MAE). From the graph, it can be seen that the DL method proposed in this article performs the best in terms of MAE, with the lowest MAE value. This means that the deviation between the predicted results of the DL method and the actual values is minimal. The RNN model follows closely behind, with relatively low MAE values, demonstrating good predictive performance. The SVM model has the highest MAE value, indicating a significant error between its predicted results and the true values.

This result further confirms the advantages of the DL method in complex tasks. The DL model, through its deep neural network structure, can automatically learn richer feature representations from raw data, thereby more accurately capturing the inherent patterns and patterns of the data. In contrast, although SVM models are powerful classification algorithms, they may not be able to fully extract and utilize key information in data when dealing with complex texture synthesis and other tasks, resulting in limited predictive performance. Although RNN models are good at processing sequential data, they may not be as effective as DL models in processing spatial data such as images.

Figure 6 visually illustrates the comparison results of these three methods in terms of training time. From the graph, it can be seen that the DL method proposed in this article takes the lowest amount of time during the training process, thanks to the efficient training algorithm and optimized network structure of the DL model. In contrast, the training time of RNN models is slightly longer, which may be due to the need for recursive computation in processing sequence data, resulting in an increase in computational complexity. The SVM model has the longest training time, which may be due to the high computational cost of solving a large-scale optimization problem during the training process. This result further confirms the efficiency advantage of the DL method. The DL model can significantly improve training speed and shorten model training time through techniques such as parallel computing and GPU acceleration.

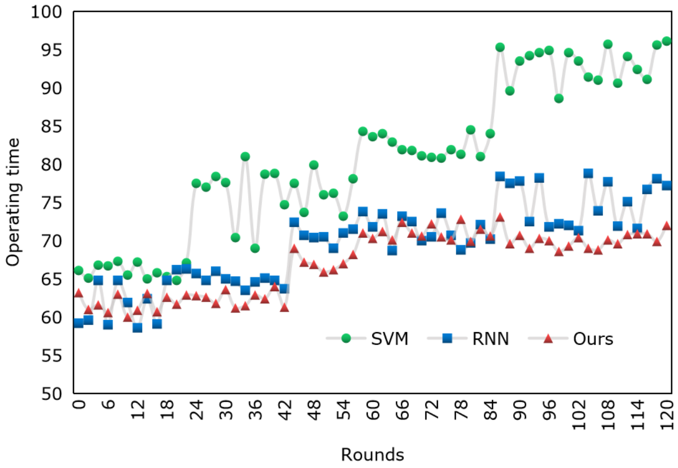

Figure 6: Time comparison of three methods.

In practical applications, this means that designers can obtain trained models faster, thereby more efficiently performing texture synthesis and product design work. It can be seen that among the SVM classification algorithm, the model based on RNN architecture, and this method, the proposed method performs best, in which the classification accuracy is over 97% and the MAE is only 1.24. Moreover, the proposed algorithm takes less time, about 0.21, which is lower than the support vector machine classification algorithm and the model based on RNN architecture of 0.61 and 0.48. The results fully demonstrate the superiority of this method.

6 CASE ANALYSIS

6.1 Model Application Process

During the model application phase, the primary consideration lies in defining the model's input and output. In the case of an architectural style classification model, the input typically consists of CAD files, architectural photographs, or various other forms of architectural data. These inputs encompass details like the building's structure, shape, and material composition, serving as the foundation for the model to determine the architectural style. The model's output represents the classification outcome, indicating the architectural style attributed to the input data. Specifically, the model identifies relevant features from the inputted architectural data and aligns them with the style characteristics acquired during training. The end result is one or more highly probable architectural style categories, ranging from specific style designations to broader classifications.

6.2 Case Analysis

The following is a typical case of the application of the architectural style classification model in the assessment and protection of ancient buildings: there are a number of precious ancient buildings in a certain area, which cover many historical periods and different architectural styles. In order to scientifically assess and protect these ancient buildings, the local Cultural Heritage Protection Department decided to use the architectural style classification model for auxiliary analysis.

First of all, the staff used drones and photographic equipment to comprehensively shoot and record ancient buildings and obtain a large number of architectural picture data. Then, they input these picture data into the architectural style classification model, which automatically classifies each picture and outputs the corresponding style category and confidence (as shown in Figure 7). By comparing the output results of the model with the assessment opinions of experts, the staff found that the model can accurately identify the style categories of ancient buildings in most cases, and can also give reasonable judgments for some more complex architectural styles. This provides strong support for the subsequent assessment and protection of ancient buildings.

Figure 7: Architectural image data and style classification.

In order to assess the effect of the model in practical application, the staff selected some representative ancient buildings for in-depth analysis. First, they invited a number of ancient architecture experts to conduct on-site inspections and assessments of these buildings and gave professional assessment opinions. Then, they compared and analyzed the expert assessment opinions with the model output results. The result is shown in Figure 8.

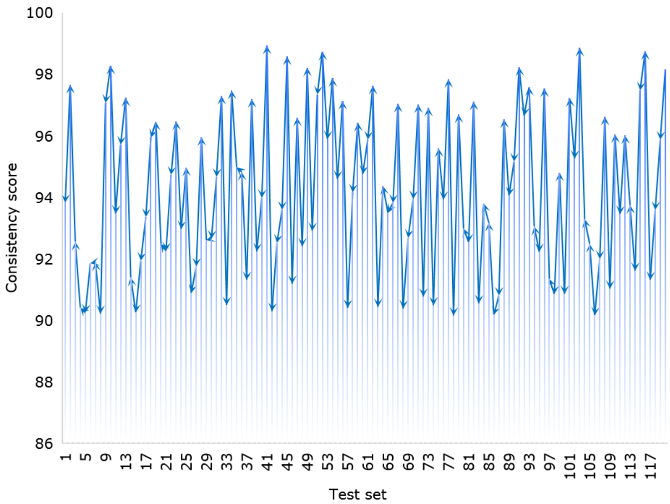

Figure 8: Consistency between model classification and expert assessment opinions.

This article carefully selected a series of representative ancient buildings as test cases. Firstly, we invited multiple experts with rich experience and professional knowledge in the field of ancient architecture to conduct detailed on-site inspections and evaluations of these buildings. They provided authoritative evaluation opinions based on key characteristics such as the age, style, and structure of the buildings. Figure 8 visually illustrates the consistency between model classification and expert evaluation opinions. From the graph, it can be seen that the classification accuracy of the model on most ancient buildings has reached over 95%, which means that the model can accurately identify the main features and types of ancient buildings, which is highly consistent with the professional judgment of experts. Although in a few cases, the model may experience misjudgments or omissions, overall, these error rates are very low and do not affect the effectiveness of the model in practical applications. These possible errors may stem from the limitations of the dataset, the complexity of the model structure, or the specificity of certain specific building features. However, this does not affect the high accuracy and stability exhibited by the model in most cases.

7 CONCLUSIONS

Following extensive research and experimentation, this article presents several significant findings. Firstly, we have successfully established a DL-driven architectural style classification model capable of efficiently and precisely recognizing and categorizing diverse architectural styles. Comparative experiments reveal that our model outperforms other classification methods across multiple evaluation metrics. Secondly, this article delves into the utilization of DL models alongside CAD technology in architectural style classification. Leveraging the precise building data afforded by CAD technology enables us to more comprehensively extract and harness structural, shape, material, and other pertinent building features. This, in turn, elevates the accuracy and generalizability of our classification model. Furthermore, the high precision and standardization inherent to CAD data enhance the efficiency and reliability of our model's training and testing phases.

In conclusion, our research underscores the tangible benefits of integrating DL models with CAD technology in architectural style classification. This amalgamation elevates classification accuracy and efficiency while paving the way for innovative approaches in architectural research and application. We are confident that as technology continues to evolve, this integration will assume a pivotal role in shaping the future of the construction industry.

Huiyu Li, https://orcid.org/0000-0001-8546-3490
Hailong Dong, https://orcid.org/0009-0005-8297-5868

REFERENCES

[1] Byun, Y.; Sohn, B.-S.: ABGS: A system for the automatic generation of building information models from two-dimensional CAD drawings, Sustainability, 12(17), 2020, 6713. https://doi.org/10.3390/su12176713
[2] Ceylan, S.: A case study on the change of students' perception of architectural design based on their knowledge of digital tools, The International Journal of Design Education, 14(2), 2019, 1-16. https://doi.org/10.18848/2325-128X/CGP/v14i02/1-16
[3] Esmaeily, Z.; Rezaeian, M.: Building roof wireframe extraction from aerial images using a three-stream deep neural network, Journal of Electronic Imaging, 32(1), 2023, 013001. https://doi.org/10.1117/1.JEI.32.1.013001
[4] Han, S.; Jiang, Y.; Huang, Y.; Wang, M.; Bai, Y.; Spool, W.-A.: Scan2drawing: use of deep learning for as-built model landscape architecture, Journal of Construction Engineering and Management, 149(5), 2023, 04023027. https://doi.org/10.1061/JCEMD4.COENG-13077
[5] Hu, L.: Application of autoCAD's 3D modeling function in industrial modeling design, Computer-Aided Design and Applications, 18(S1), 2021, 33-42. https://doi.org/10.14733/cadaps.2021.S1.33-42

[6] Krner, A.; Born, L.; Bucklin, O.: Integrative design and fabrication methodology for bio-inspired folding mechanisms for architectural applications, Computer-Aided Design, 133(80), 2020, 102988. https://doi.org/10.1016/j.cad.2020.102988
[7] Livshits, I.-L.; Glebovskyi, A.-S.; Protsuto, M.-V.: Interdisciplinary approach for simulation of starting points for optical and architectural design, Advanced Optical Technologies, 8(2), 2019, 135-144. https://doi.org/10.1515/aot-2018-0062
[8] Makransky, G.; Petersen, G.-B.: Investigating the process of learning with desktop virtual reality: a structural equation modeling approach, Computers & Education, 13(46), 2019, 15-30. https://doi.org/10.1016/j.compedu.2019.02.002
[9] Nie, Y.; Hu, L.; Zhang, J.: Feature matching based on grid and multi-density for ancient architectural images, Journal of Computer-Aided Design and Computer Graphics, 32(3), 2020, 437-444. https://doi.org/10.3724/SP.J.1089.2020.17835
[10] Nysetvold, J.; Salmon, J.: Assessment of user preferences for 3d modeling and design reviews in virtual reality, Computer-Aided Design and Applications, 18(5), 2021, 1035-1049. https://doi.org/10.14733/cadaps.2021.1035-1049
[11] Tai, N.-C.; Sung, L.-W.: Digital archiving of perceptual experiences of an architectural space with computer-aided methods, Computer-Aided Design and Applications, 17(3), 2019, 585-597. https://doi.org/10.14733/cadaps.2020.585-597
[12] Tastan, H.; Tong, T.; Tuker, C.: Using handheld user interface and direct manipulation for architectural modeling in immersive virtual reality: An exploratory study, Computer Applications in Engineering Education, 30(2), 2022, 415-434. https://doi.org/10.1002/cae.22463
[13] Xin, W.; Daping, Q.: Digitalization system of ancient architecture decoration art based on neural network and image features, Journal of Intelligent & Fuzzy Systems, 40(2), 2021, 2589-2600. https://doi.org/10.3233/JIFS-189251
[14] Zhang, X.; Yao, J.; Dong, L.; Ye, N.: Research on 3D architectural scenes construction technology based on augmented reality, Journal of Computational Methods in Sciences and Engineering, 21(2), 2021, 311-327. https://doi.org/10.3233/JCM-204390
[15] Zhou, Q.: Research on architectural space design of coastal cities based on virtual reality technology, Journal of Coastal Research, 11(51), 2020, 13. https://doi.org/10.2112/JCR-SI115-005.1