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

Extracting Architectural Design Elements of CAD Data Using Deep Learning Algorithms

Zhenliang Wang[1] and Dan Wang[2]

[1]School of Ceramics, Pingdingshan University, Pingdingshan, Henan 467000, China, 6402@pdsu.edu.cn
[2]School of Art and Design College, Henan University of Urban Construction, Pingdingshan, Henan 467000, China, 20192041@huuc.edu.cn

Corresponding author: Zhenliang Wang, 6402@pdsu.edu.cn

Abstract. In computer-aided design (CAD) data, architectural design elements usually exist in various forms, such as graphics, lines, and texts. Extracting these design elements efficiently and accurately from massive CAD data and applying them to architectural design practice is a difficult problem in architectural design. In this article, deep learning (DL) and fuzzy C clustering (FCM) algorithms in data mining (DM) are combined to extract architectural design elements from CAD data, predict the required architectural features, and provide support for the intelligent development of architectural design. By comparing the recall and accuracy, it is found that the algorithm can effectively identify the actual architectural features and has a high proportion of real cases in the samples predicted as positive cases. This shows that the algorithm can not only capture the architectural features but also effectively eliminate the interference factors and reduce the occurrence of false positives. This method improves the performance of extracting design elements and provides reliable technical support for intelligent architectural design and promotes cross-domain innovation and development.

Keywords: Deep Learning; CAD; Architectural Design; Data Mining; FCM Algorithm
DOI: https://doi.org/10.14733/cadaps.2024.S19.179-193

1 INTRODUCTION

With the wide application of CAD in architectural design, a large amount of CAD data has become an indispensable information resource for designers, engineers, and related researchers. These CAD data contain rich architectural design elements, which not only reflect the creative ideas of architects but also reflect the functional requirements, structural characteristics, and aesthetic value of buildings. Traditional architectural design methods often rely on the experience and intuition of designers, while deep learning algorithms can automatically extract features and discover patterns through learning from large amounts of data, providing more diverse solutions for architectural design. Berseth et al. [1] explored how to use deep learning algorithms to design interactive architectural elements and explore diverse solutions. Interactive architectural elements are an important direction for future architectural design. It explores how to use deep learning algorithms to design interactive architectural elements and explores diverse solutions. The application of deep learning algorithms will bring more possibilities to architectural design, making it more intelligent and personalized. In the future, with the continuous development of deep learning technology, its application in the field of architectural design will be more extensive, and the design of interactive architectural elements will also become more diverse and intelligent. With the continuous development of digital technology, the field of architectural design is also undergoing tremendous changes. The application of digital tools makes architectural design more efficient, precise, and creative. At the same time, students' perception of architectural design has also changed. Ceylan [2] explores the changes in students' perception of architectural design based on digital tool knowledge through a case study. In order to further explore the changes in students' perception of architectural design, they selected an architectural design course as the case study object. This course adopts digital tools for teaching, focusing on cultivating students' innovative thinking and practical abilities. Through questionnaire surveys and interviews, it was found that students exhibit higher learning enthusiasm and participation in the course, and their perception of architectural design is more comprehensive and in-depth. Through the study of case studies, we can conclude that the changes in students' perception of architectural design based on digital tool knowledge are mainly reflected in design innovation, structural understanding, and attention to environmental sustainability. The application of digital tools not only enhances students' design abilities but also broadens their understanding and cognition of architectural design. Extracting these design elements efficiently and accurately from massive CAD data and applying them to architectural design practice is a difficult problem in architectural design. The rapid rise of the DL algorithm provides a new solution for CAD data analysis. DL algorithm can automatically learn the deep features in data and identify complex patterns efficiently. Applying the DL algorithm to CAD data analysis is expected to realize automatic extraction and intelligent identification of architectural design elements.

With the acceleration of urbanization, the number of road construction projects is increasing, and identifying and analyzing road scenes has become an important task. In order to better manage and utilize road engineering construction data, Chen et al. [3] proposed a multi-label architecture for building engineering data mining based on CAD (computer-aided design), aiming to improve the accuracy and efficiency of road scene recognition. A multi-label architecture is an architecture that applies multiple labels to the same data object in order to better describe and classify the features and attributes of the object. In road scene recognition, multi-label architecture can help us better understand and analyze road engineering construction data, including road shape, size, materials, construction technology, etc. It utilizes computer vision and image processing techniques to extract features related to road scenes, such as lines, shapes, textures, etc., from preprocessed data. The experimental results show that this architecture can effectively improve the accuracy and efficiency of road scene recognition while reducing manual intervention and errors. With the popularization of 3D laser scanning technology, we are able to obtain a large amount of point cloud data. These data can provide detailed and non-destructive 3D views of architectural heritage. However, extracting meaningful information from these point cloud data is a challenging task. Croce et al. [4] proposed a semiautomatic method based on machine learning to extract information on heritage building elements from semantic point clouds and establish an information model. The feasibility and effectiveness of this method were verified through experiments using 3D laser scanning data from historical buildings. The experimental results show that this method can accurately identify different architectural elements and establish a detailed information model. Compared with traditional semiautomatic or manual methods, this method greatly improves the efficiency and accuracy of information extraction. In CAD data, architectural design elements usually exist in various forms, such as graphics, lines, texts, etc., and there may be complex spatial relations and attribute relations between them. To extract these elements accurately, it is necessary to build a DL model that can deeply understand the internal structure and semantic information of CAD data. Such a model should have a strong ability for feature learning and classification and can adaptively learn various design elements in CAD data and accurately map them into the predefined architectural feature space. FCM algorithm provides a powerful auxiliary tool for DL. FCM algorithm is a clustering analysis method based on fuzzy theory, which can find uncertain and fuzzy clustering structures in data sets. In architectural design, the boundaries between many design elements are not completely clear, but there is a certain fuzziness and relevance. By introducing the FCM algorithm, these fuzzy design elements can be organized and classified more reasonably, thus improving the understanding and recognition ability of the DL model to CAD data.

The combination of blockchain technology and Building Information Modeling (BIM) has brought new opportunities and challenges to architectural design. Douglas et al. [5] explored how to build a decentralized architectural design framework based on blockchain and BIM and analyzed its computational problems in practical applications. Using blockchain technology, build a decentralized data storage platform to ensure the authenticity and immutability of data. By using BIM models, building information is stored digitally on the blockchain. Due to the large amount of data involved in architectural design, how to efficiently store and process this data on the blockchain is a key issue. The solution may include using distributed storage technology, optimizing data structures, etc. Multiple participants need to collaborate on design at the same time, which requires strong computing power to support real-time data synchronization and updates. Cloud computing and edge computing technologies can play an important role in this regard. The goal of this study is to combine DL with the FCM algorithm to construct an efficient and accurate CAD data analysis framework and realize the task of automatically extracting architectural design elements from CAD data. This article will build a DL-based CAD data processing model, which can automatically learn the deep features in CAD data and realize intelligent identification of design elements. On this basis, the FCM algorithm is introduced, and the identified design elements are analyzed by fuzzy clustering so as to reveal their internal relationship and fuzzy structure. By integrating DL with the FCM algorithm, we aim to achieve automatic, efficient, and precise extraction of architectural design elements from CAD data. This integration offers robust technical support for the intelligent advancement of architectural design, ultimately enhancing design efficiency, alleviating the workload of designers, and propelling the digital transformation and intelligent upgrading of the architectural design industry. Specifically, this article introduces the following innovations:

(1) This article applies the DL algorithm to the analysis of CAD data, which breaks through the limitations of traditional CAD data processing methods.

(2) This article constructs a DL-based CAD data processing model, which can automatically learn the deep features in CAD data and realize the intelligent identification of architectural design elements.

(3) in architectural design, the boundaries between many design elements are vague and related. In this article, the FCM algorithm is introduced, and the identified design elements are analyzed by fuzzy clustering, revealing their internal relationship and fuzzy structure.

This article first introduces the research background and significance of extracting architectural design elements from CAD data by using the DL algorithm and then expounds in detail the methodological framework of combining DL and FCM algorithm, including key steps such as analysis of CAD data characteristics, construction of DL model and application of FCM algorithm. Subsequently, the validity of the proposed method is verified, and its application prospect in the intelligent development of architectural design is discussed. Finally, the full text is summarized and prospected, and the main achievements and possible research directions in the future are summarized.

2 RELATED WORK

3D CAD (computer-aided design) technology has become an indispensable part of ship and offshore structure construction. The rise of augmented/virtual reality (AR/VR) technology enables us to display and manipulate 3D CAD data more intuitively and realistically. Han et al. [6] explored how to extract and transform data from 3D CAD data and how to apply this data to augmented/virtual reality to optimize the construction process of ships and offshore structures. In addition to geometric information, it is also necessary to extract and fuse attribute information related to ships or offshore structures, such as material type, color, texture, etc. These pieces of information will be used to enhance the visual effects of the virtual model. By utilizing AR/VR technology, engineers can perform virtual assembly and simulation before actual construction. This helps to identify potential issues in the design and reduce errors and costs in actual construction. With the continuous development of machine vision technology, image matching has been widely applied in many fields, such as remote sensing image analysis, cultural relic identification, and ancient building protection. Among them, image matching of ancient Chinese architecture is of great significance for the protection and restoration of ancient architecture. Hu et al. [7] introduced a grid and multi-density-based method for matching ancient Chinese architectural images, which can quickly and accurately extract and match the features of ancient buildings. The grid-based feature extraction method divides the image into several equally sized grids, each representing a region of the image. By calculating the pixel features within each grid, the overall and local features of the image can be extracted. In ancient building image matching, we can select suitable pixel features for extraction based on the shape, structure, and texture characteristics of ancient buildings, such as color, texture, edges, etc. Grid-based feature extraction methods can quickly process large-scale image data and improve the efficiency of feature extraction.

With the continuous development of digitalization and information technology, Building Information Modeling (BIM) has been widely applied in infrastructure design and construction. However, due to diverse data sources and uneven data quality, there are often errors in element-to-entity mapping in BIM data. These errors may lead to project decision-making errors, chaotic construction processes, and difficulties in later maintenance. Therefore, it is particularly important to check the correctness of element-to-entity mapping on BIM data. Koo et al. [8] proposed a method based on geometric deep learning to check the accuracy of element-to-entity mapping in infrastructure-building information models. This method is mainly based on geometric deep learning technology, which trains deep neural networks to recognize and predict the relationships between elements and entities in BIM data. Through training and learning, the network is able to learn the mapping relationship between elements and entities. The application of biomimetic design in various fields is becoming increasingly widespread. In the field of architecture, bionic design not only has aesthetic value but also provides innovative building structures and functions. Among them, as a new type of architectural design element, the integrated design and manufacturing methods of biomimetic folding mechanisms have become a hot research topic. Krner et al. [9] explored the integrated design and manufacturing methods of biomimetic folding mechanisms in architectural applications. The design inspiration for biomimetic folding mechanisms comes from organisms in nature, such as butterfly wings and turtle shells. These organisms achieve lightweight, sturdy, and environmentally friendly characteristics through their unique folding methods. In architectural design, biomimetic folding mechanisms draw inspiration from the folding principles of these organisms and achieve innovation in building structures through precise calculations and design. Taking a biomimetic folding structure building as an example, introduce its integrated design and manufacturing process. Firstly, design the structure according to the building requirements and optimize it using computer simulation technology. Then, select appropriate materials and processes for manufacturing. Finally, the finished product is tested and accepted to ensure that its performance and stability meet the requirements.

By utilizing deep learning frameworks, it is possible to quickly and accurately collect relevant data on architectural conceptual design, such as spatial layout and structural relationships. These data are processed and analyzed to provide basic information for topology algorithms. By utilizing algorithms such as Convolutional Neural Networks (CNN) in deep learning frameworks, feature extraction can be performed on architectural conceptual design data. Representative topological features are extracted by analyzing the geometric features and structural relationships of spatial form. Based on the extracted topological features, construct a topological model using a deep learning framework. This model can describe the topological relationships and evolutionary laws of spatial form, providing guidance for architectural conceptual design. Taking an innovative building project as an example, Lin [10] used a deep learning framework to develop topology algorithms for architectural conceptual design. It utilized a deep learning framework to collect relevant data on architectural conceptual design. Then, build a topology model based on the data. Next, use a deep learning framework to train and optimize the model. Finally, the architectural concept design is carried out through the generated topological form. Livshits et al. [11] explored the interdisciplinary analysis of architectural design elements based on fuzzy C-clustering for simulating the starting point of architectural design. Fuzzy C-clustering is a clustering analysis method based on fuzzy theory, which can effectively handle data with uncertainty and fuzziness. In architectural design, fuzzy C-clustering can be applied to the classification and recognition of architectural elements, helping designers better understand and analyze design problems. Through fuzzy C-clustering, architectural elements can be classified, and design optimization and decision-making can be made based on different classifications. Taking an actual construction project as an example, this article introduces how to apply fuzzy C clustering for interdisciplinary analysis of architectural design elements. Firstly, collect and organize project-related data and information, including functional requirements, formal expressions, materials and technologies, environmental impacts, and socio-cultural factors. Then, fuzzy C-clustering will be used to classify and identify these elements, key factors, and potential problems. Finally, based on the results of the analysis, design optimization, and decision-making are carried out to achieve a more reasonable and effective architectural design.

Computer-aided design software such as Auto CAD has been widely used in the construction industry. This software not only improves the accuracy and efficiency of design but also leaves behind a large amount of design data. How to extract useful information from these data and provide inspiration and reference for architectural color and style design has become a topic worth exploring. Ma et al. [12] explored how to use Auto CAD data for data mining and extract architectural color and style elements. It utilizes data mining techniques to extract features related to architectural color and style from preprocessed data. These features may include color, texture, shape, etc., which can reflect the style and characteristics of architectural design. Perform pattern recognition and classification on the extracted features through machine learning algorithms. By training classifiers, different architectural color styles can be classified into different categories, making it convenient for subsequent element extraction and analysis. Taking a construction project in a certain region as an example, using Auto CAD data for data mining to extract architectural color and style elements. Using machine learning algorithms for pattern recognition and classification. Finally, based on the classification results, specific architectural color and style elements are extracted and presented through visualization techniques. The development of satellite remote sensing and deep learning technology has made it possible to construct 3D city models from satellite stereo images. This method is of great significance for urban planning, disaster assessment, environmental protection, and other fields. Pepe et al. [13] introduced a new method based on deep learning, GIS, and geoscience software for constructing 3D city models from VHR (high-resolution) satellite stereo images. This method is mainly based on deep learning technology, which automatically extracts three-dimensional structural information from satellite stereo images by training deep neural networks. At the same time, by combining GIS (Geographic Information System) and geoscience software, the extracted three-dimensional structural information is integrated and optimized to construct an accurate 3D urban model. The experimental results show that this method can automatically extract three-dimensional structural information from VHR satellite stereo images and construct a high-precision 3D city model. Compared with traditional manual or semiautomatic methods, this method greatly improves modeling efficiency and accuracy.

The visual attention mechanism is an effective way of filtering and integrating information, which can help people quickly locate areas of interest in complex architectural visual scenes. In the task of building image annotation, introducing a visual attention mechanism can guide the model to focus on key areas in the building image, thereby improving the accuracy and efficiency of annotation. Common visual attention mechanisms include feature-based attention models and meta-learning-based attention models. In this article, Zhang et al. [14] used a feature-based attention model to automatically identify and annotate key areas in the image by learning the correlation between building image features and annotations. Graph convolutional network is a deep learning model designed specifically for graph data, which can effectively handle complex structured data such as nodes, edges, and faces. Then, the graph convolutional network is used to perform convolution operations on the architectural graphics, extracting spatial features and contextual information from the architectural images. By combining visual attention mechanisms and graph convolutional networks, we can better capture semantic information in architectural images and improve annotation accuracy. The three-dimensional form of buildings not only affects the urban landscape but may also have an impact on environmental factors such as atmospheric soil energy processes, temperature, and relative humidity. Deep learning algorithms have significant advantages in processing large-scale data and complex models, providing powerful tools for analyzing such impacts. Zhen et al. [15] explored how to use deep learning algorithms to analyze the impact of three-dimensional building forms on the environment. Deep learning algorithms require a large amount of data for training. Collect spatiotemporal data of buildings and their surrounding environment through various methods such as satellite remote sensing, ground observation, and numerical simulation. It trains deep learning models using collected and processed data. During the training process, continuously adjust the model parameters to minimize prediction errors. Gradually improve the prediction accuracy of the model through optimization algorithms such as backpropagation and gradient descent. Use the trained model to predict new building form data and analyze its impact on atmospheric soil energy processes, temperature, and relative humidity. Evaluate the prediction accuracy and reliability of the model by comparing the predicted results with actual observation data.

3 DL-BASED CAD DATA PROCESSING MODEL

3.1 DL Theoretical Basis

CAD data, as the core tool of modern architectural design, has characteristics and manifestations that are very important for the extraction of architectural design elements. CAD data not only contains basic information such as geometric shape, size, and location of buildings but also involves non-geometric properties such as materials, colors, and textures, which together constitute the rich connotation of architectural design. In a CAD system, every design element is accurately expressed in digital form, and whether it is the length of a line segment, the radian of a curve, or the area of a surface, it can achieve extremely high accuracy. At the same time, CAD data follow certain standards and specifications, such as DWG, DXF, and other formats. These formats stipulate the way of data organization and storage so that different CAD systems can exchange and share data with each other. In CAD systems, architectural design elements are usually organized in the form of hierarchical structures, such as buildings, floors, rooms, doors, and windows. In addition, there are complex relationships between elements in CAD data, such as the relationship between dimensions and geometry and the relationship between doors and windows and walls. Graphics are the most basic representation of CAD data, including 2D graphics such as line segments, arcs, polygons, and 3D solid models. These graphics intuitively show the shape and appearance of architectural design, which is the main basis for designers to carry out creative ideas and scheme comparisons. Symbols are graphic marks used to represent specific design elements in CAD data, such as door and window symbols, labeling symbols, and so on. The use of symbols not only simplifies the complexity of graphics but also improves the readability and understandability of design information.

Architectural design elements are the basic units of architectural design, and they are reflected in various forms in CAD data. These design elements not only include basic information such as the geometric shape, size, and location of the building but also involve non-geometric attributes such as the material, color, and texture of the building. In terms of geometric shape, architectural design elements are mainly embodied in basic graphic elements such as points, lines, and surfaces. Point is one of the most basic elements in CAD data, which represents the position information. A line is an infinitely extending geometric figure determined by two points, which is used to represent contours, boundaries, and so on in CAD data. A face is a closed area determined by three or more points, which is used to represent entities, sections, etc., in CAD data. These basic graphic elements form complex architectural design shapes through combination and transformation. In terms of non-geometric attributes, architectural design elements are mainly embodied in attribute information such as materials, colors, and textures. Material information reflects the material composition of architectural design, such as concrete, steel, wood, etc. Color information endows architectural design with visual color characteristics; Texture information is used to simulate the texture and details of the building surface. These non-geometric attribute information usually exist in the form of layers, styles, and attribute sets in CAD data, and they combine with geometric shape information to form a complete description of architectural design. In recent years, Deep Learning (DL), a subset of machine learning, has attained noteworthy accomplishments in the domains of computer vision and natural language processing. Its powerful feature learning and classification capabilities make the DL algorithm show its unique advantages in dealing with complex data. In CAD data processing, the DL algorithm can automatically learn the deep features in data and realize intelligent identification of design elements.

The core idea of DL is to build a multi-layer neural network model and extract features from data by learning layer by layer. These features are gradually abstracted from the bottom to the top, and finally, a comprehensive description of the data is formed. In the process of CAD data processing, the DL model can automatically learn basic information such as geometric shape, size, and position, as well as non-geometric attributes such as materials, colors, and textures in CAD data, thus realizing a comprehensive understanding of architectural design elements.

The convolutional neural network has obvious advantages in processing image data. It can automatically learn local features and global features in images by alternately stacking convolution layers and pooling layers. A cyclic neural network is suitable for processing sequence data, such as text, voice, etc. It captures the time sequence information in the sequence through a cyclic connection. Self-encoder is an unsupervised learning algorithm that compresses and reconstructs data through the combination of encoder and decoder, thus learning the internal structure of data. According to the characteristics of CAD data, this article chooses a convolutional neural network as the basic structure of the DL model. By constructing a multi-layer convolution layer and pool layer, the geometric shape and non-geometric properties of CAD data can be automatically learned. At the same time, in order to capture the time series information and correlation in CAD data, this article will also introduce the structure of circular neural networks into the model.

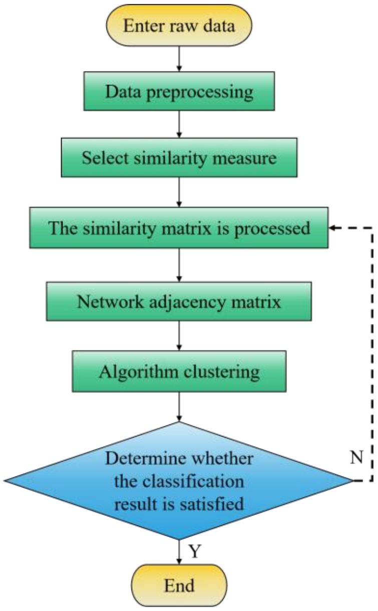

Figure 1: DM and clustering algorithm flow of CAD.

3.2 Model Architecture Design and Parameter Selection

The DL-based CAD data processing model comprises several layers, each serving a distinct purpose. The input layer receives raw CAD data and converts it to a format compatible with the neural network. The convolution layer, utilizing multiple convolution kernels, learns both local and global features from the CAD data, extracting diverse characteristics. The recurrent layer captures sequential information and correlations within the CAD data, processing this sequential data through recurrent connections. The fully connected layer integrates the features garnered from preceding layers, creating a comprehensive representation of the CAD data. Finally, the output layer outputs the model's processing results for CAD data, such as the identification and classification of architectural design elements. The flow chart of DM and the clustering algorithm of CAD is shown in Figure 1.

Consider the following collection of elements intended for classification:

$$X = \left[X_1, X_2, \cdots, X_n\right] \tag{1}$$

Every element possesses s indicators as follows:

$$X_j = \left[x_{j1}, x_{j2}, \cdots, x_{js}\right], j = 1,2,\cdots,n \tag{2}$$

Assign the classification number c, thereby enabling the utilization of a $c \times n$--order matrix U to denote the degree of membership for each individual element.

$$U = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ u_{c1} & u_{c2} & \cdots & u_{cn} \end{bmatrix} \tag{3}$$

The goal function outlined for ambiguous categorization is as follows:

$$\arccos\ N_{new} \cdot N_{ini} \ \le \varepsilon \tag{4}$$

In this context, $Z = \ z_1, \cdots, z_n$ it is assigned a value of 1, z_j denotes the center of the cluster for the $j\ \ j = 1,2,\cdots,c$ -class, m serves as the weighting coefficient, and represents the Euclidean distance measured from the sample point x_i to the center point z_j.

Constraints associated with the clustering objective function are outlined below:

$$\sum_{i=1}^{c} u_{ik} = 1, \forall_k \tag{5}$$

When selecting model parameters, key considerations include the convolution kernel size, the count of convolution layers, the number of recurrent layers, and the neuron count in the fully connected layer. The convolution kernel size dictates the range of features extractable by the convolution layer; typically, smaller kernels excel at capturing local features. The number of convolution layers defines the depth and abstraction level of the model's learned features. While increasing these layers enhances the model's feature-learning capabilities, it also elevates its complexity and computational demands. The number of recurrent layers influences the model's ability to capture the length and relevance of time-series information; augmenting them bolsters the model's sequencing prowess. Lastly, the neuron count in the fully connected layer determines how well the model integrates features from preceding layers. Too many neurons may lead to over-fitting, while too few neurons may lead to under-fitting. The feature detection model of architectural design CAD image based on DL is shown in Figure 2.

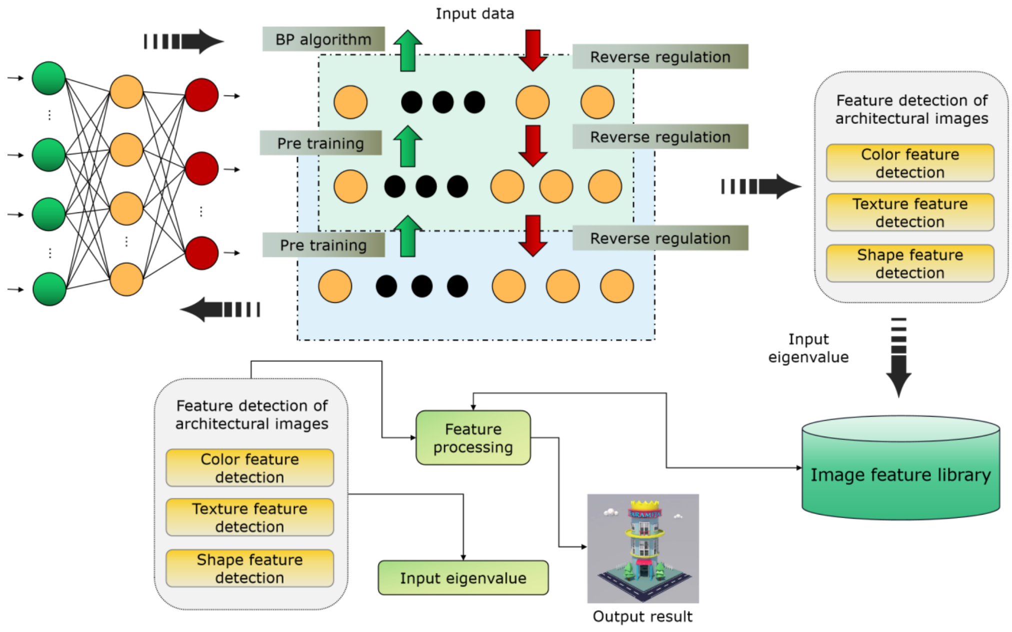

Figure 2: Feature detection model of architectural design CAD image.

3.3 Model Training and Optimization Strategy

In the aspect of model training, this article adopts supervised learning to train. Firstly, a large number of CAD data and corresponding architectural design element labels are collected as training samples, and then the training samples are input into the model for training. In the training process, the error between the model output and the label is calculated by the backpropagation algorithm, and the parameters of the model are adjusted according to the error so that the model can gradually learn the ability to extract architectural design elements from CAD data.

In order to optimize the training process and improve the performance of the model, this article adopts a variety of optimization strategies. The first is the data enhancement strategy, which generates more training samples by rotating, translating, and scaling the original CAD data, thus enhancing the generalization ability of the model. Secondly, the regularization strategy, by adding a regularization term to the model to prevent the occurrence of over-fitting, improves the robustness of the model. In addition, the dynamic learning rate strategy is adopted to adjust the learning rate dynamically according to the training situation of the model to accelerate the convergence speed of the model.

4 APPLICATION OF FCM ALGORITHM IN THE EXTRACTION OF ARCHITECTURAL DESIGN ELEMENTS

4.1 Principle and Characteristics of FCM Algorithm

The FCM algorithm represents a clustering technique rooted in fuzzy mathematics theory. Unlike traditional clustering methods, where data points are strictly assigned to a single cluster, the FCM approach allows for data points to belong to multiple clusters with varying degrees of membership. This flexibility proves particularly advantageous when dealing with uncertain or fuzzy datasets.

In the context of architectural design element extraction, the application of the FCM algorithm is highly significant. Given the intricate relationships and inherent fuzziness among design elements, traditional clustering techniques often struggle to delineate boundaries precisely. The FCM algorithm, however, excels at grouping design elements with shared characteristics into cohesive clusters by calculating fuzzy membership values between data points. This enables a more nuanced analysis of architectural design elements through fuzzy clustering.

The fundamental principle behind the FCM algorithm is to simultaneously maximize intra-cluster similarity while minimizing inter-cluster similarity. Through an iterative optimization process, the algorithm refines the membership degrees and cluster centers of data points, striving to achieve the highest sum of membership degrees for each data point within its designated cluster while minimizing these sums for other clusters. This iterative process continues until a stable clustering solution emerges, characterized by minimal changes in the fuzzy partition matrix and cluster centers.

4.2 Fuzzy Clustering Analysis Process of Design Elements

In the process of extracting architectural design elements, the initial step involves preprocessing the original CAD data. This includes tasks such as data cleaning, format conversion, and feature detection. The number of clusters, which reflects the anticipated number of groupings, can be adjusted based on specific needs. The fuzzy factor, typically ranging between 1.5 and 2.5, determines the degree of fuzziness in data point allocation to clusters. Meanwhile, the maximum number of iterations serves as a control for the algorithm's convergence speed. Utilizing the extracted features of design elements, the fuzzy similarity between data points is assessed and compiled into a fuzzy similarity matrix. This similarity can be quantified using various distance metrics. With the fuzzy similarity matrix in place, the iterative procedure for fuzzy clustering commences. Each iteration involves calculating the membership degree of each data point relative to every cluster center based on the current fuzzy partition matrix and cluster centers. Subsequently, both the fuzzy partition matrix and cluster centers undergo updates. This iterative process aims to maximize intra-cluster similarity while minimizing inter-cluster similarity. The multi-classifier system developed in this context is visually represented in Figure 3.

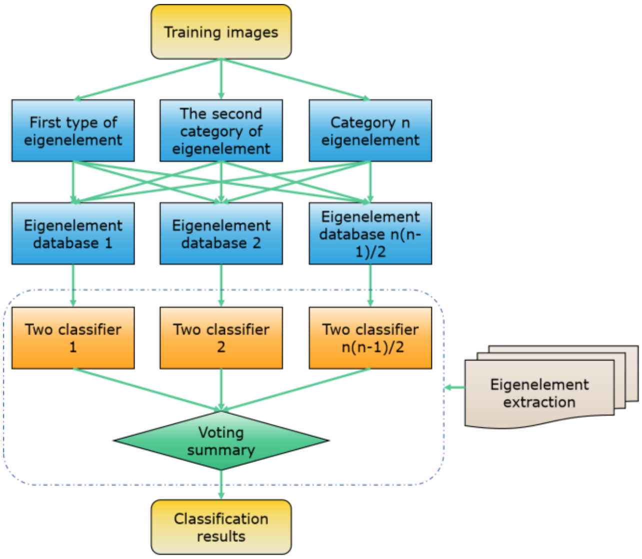

Figure 3: Multi-classification system.

To depict the distribution of distances between clusters in clustering outcomes, we may employ two metrics: the inter-class distance with criterion G_{b1} and the weighted inter-class distance with criterion G_{b2}. These are defined as follows:

$$G_{b1}=\sum_{j=1}^{c}(m_j-m)^T(m_j-m) \tag{6}$$

$$G_{b2}=\sum_{j=1}^{c}p_j(m_j-m)^T(m_j-m) \tag{7}$$

In this context, m_j represents the average sample vector for cluster j, m denotes the mean vector encompassing all samples, and p_j corresponds to the prior probability associated with cluster j.

The FCM algorithm divides X into C subsets $S_1,S_2,\cdots,S_c$. It $V=\{v_1,v_2,\cdots,v_c\}$ is the clustering center of these c subsets and u_{ki} ($u_{ki}\in[0,1]$) is the membership degree of the i-th object belonging to the k-th class, the objective function of the FCM algorithm is:

$$J_m(U,V)=\sum_{k=1}^{c}\sum_{i=1}^{n}u_{ki}^{m}d_{ik}^{2}=\sum_{k=1}^{c}\sum_{i=1}^{n}u_{ki}^{m}\left\|x_i-v_k\right\|^2 \tag{8}$$

The FCM algorithm boasts a straightforward structure and is capable of addressing clustering challenges through the optimization of the objective function. Its fundamental concept, which revolves around the fuzzy membership degree of samples, effectively caters to real-world problem demands through the application of optimization theory in calculations and analyses.

When the iterative process converges or reaches the maximum number of iterations, the final fuzzy clustering result is output. The results include a fuzzy partition matrix and cluster center, which can be used to describe the degree to which each design element belongs to each cluster and the position of the center point of the cluster. The output fuzzy clustering results are post-processed and applied. Post-processing includes result visualization, clustering performance evaluation, etc., which can display clustering results in an intuitive way and assess the accuracy and effectiveness of clustering. In application, the FCM algorithm can be applied to the tasks of extraction, classification, and organization of architectural design elements, which provides support for the intelligent development of architectural design.

Consider the data set of s dimensions as follows:

$$X=\{x_1,x_2,\cdots,x_n\}\subset R^s \tag{9}$$

Where n represents the count of elements within the dataset and k denotes the initial number of clusters. The Euclidean distance between a sample point x_i and the center of a cluster v_j is calculated as:

$$d_{ij}=d(x_i,v_j)=\left\|x_i-v_j\right\| \tag{10}$$

μ_{ij} Represents the membership value of the i sample point belonging to a class while $U=\{\mu_{ij}\}$ is an $n\times k$ -dimensional membership matrix. The clustering criterion function GD is defined as follows:

$$GD=\frac{\sum_{i,j=1}^{k}Ds_{ij}}{\sum_{j=1}^{k}Gr_j} \tag{11}$$

Within this context, Ds_{ij} denotes the measure of proximity between the i th and j th information particles, whereas Gr_j represents the coupling measure associated with the j th information particle.

5 RESULT ANALYSIS AND DISCUSSION

In data analysis, for quantitative data, especially those with large differences in data distribution intervals, the direct analysis may ignore some important information because this information may be covered by extreme values or abnormal values of data. In order to avoid this situation, it is an effective method to discretize the data. Interval discretization can divide continuous data into several discrete intervals so that the data in each interval has similar characteristics or meanings. Figure 4 shows the results of discretization of data intervals.

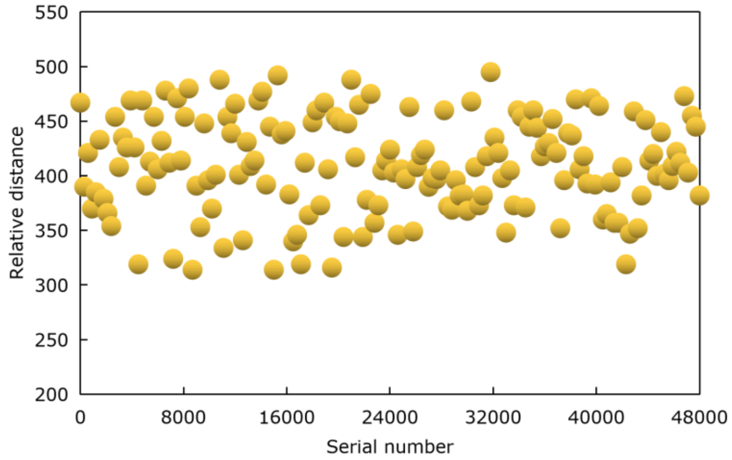

Figure 4: Data De-outlier processing.

When the data distribution interval is quite different, interval discretization is helpful to balance the influence of different data points. In the discretized interval, each data point has the same contribution to the interval and will not have too much influence because of its numerical value. In this way, those special data, even if their values are extreme, will not be completely eliminated but will be reasonably allocated to the corresponding interval.

Converting a 3D entity into stippling is a mapping process from 3D to 2D, as shown in Figure 5. First of all, there needs to be a 3D solid model, which can be created by 3D modeling software or obtained by 3D scanning technology. Models usually consist of vertices, edges, and faces, which define the shape and structure of objects. Choose a perspective to observe the 3D entity, which determines the appearance of the object in the final 2D image. The choice of viewing angle can be based on the required visual effect or practical application requirements. In order to simulate the lighting conditions in the real world, it is necessary to set up a light source in the virtual scene. The position, intensity, and color of the light source will affect the final representation of objects in 2D images. Using 3D graphics rendering technology, such as ray tracing or rasterization, the 3D solid model is rendered into a 2D image according to the selected viewing angle and lighting conditions. Details such as color, shadow, and texture of objects are calculated during rendering. After the rendering is completed, a 2D image is obtained, which reflects the appearance of a 3D entity observed from a specific perspective.

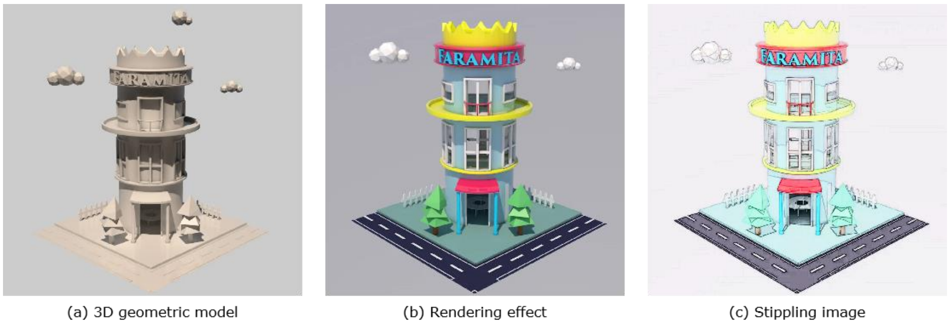

Figure 5: A stippling sketch is generated from an image rendered by a 3D entity.

In the prediction of architectural features, the recall and accuracy of comparison algorithms are important indexes to assess their performance. The recall measures the ability of the algorithm to find real cases, while the accuracy rate measures how many of the samples predicted as positive cases are real positive cases. Figures 6 and 7 show the performance of the algorithm in recall and accuracy, respectively.

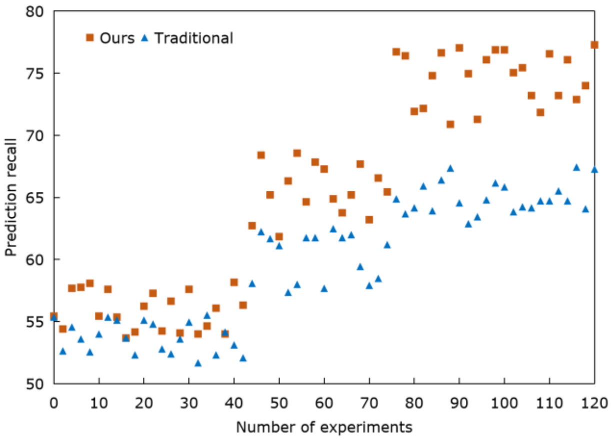

Figure 6: Comparison of predicted recall.

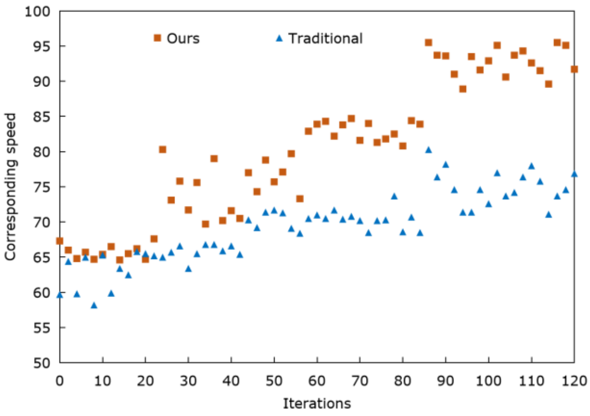

Figure 7: Comparison of prediction accuracy.

Combining the results of Figure 6 and Figure 7, it can be seen that the algorithm has achieved good performance in building feature prediction. The improvement in recall and accuracy shows the superiority of the algorithm in identifying architectural features. The improvement of this performance may benefit from the design and optimization of the algorithm, which can capture the feature information more accurately and effectively eliminate the interference factors when dealing with the task of building feature prediction.

6 CONCLUSION

In CAD data, architectural design elements usually exist in various forms, such as graphics, lines, texts, etc., and there may be complex spatial relations and attribute relations between them. Architectural design elements are the basic units of architectural design, and they are reflected in various forms in CAD data. This article will build a DL-based CAD data processing model, which can automatically learn the deep features in CAD data and realize intelligent identification of design elements. On this basis, the FCM algorithm is introduced, and the identified design elements are analyzed by fuzzy clustering so as to reveal their internal relationship and fuzzy structure. The algorithm shows excellent performance in the task of building feature prediction. By comparing the recall and accuracy, it is found that the algorithm can not only effectively identify the actual architectural features but also has a high proportion of real cases in the samples predicted as positive cases. This shows that the algorithm can not only capture the architectural features but also effectively eliminate the interference factors and reduce the occurrence of false positives.

Although the algorithm has achieved good performance in recall and accuracy, it may still have some limitations. For example, in some specific scenes, the algorithm may not be able to accurately predict some complex architectural features or be affected by factors such as image quality and lighting conditions, resulting in errors. Therefore, in practical application, it is necessary to further optimize and improve the algorithm according to the specific situation to improve its adaptability and accuracy in various scenarios.

Zhenliang Wang, https://orcid.org/0009-0000-7901-2212
Dan Wang, https://orcid.org/0009-0006-1078-6280

REFERENCES

[1] Berseth, G.; Haworth, B.; Usman, M.; Schaumann, D.; Khayatkhoei, M.; Kapadia, M.; Faloutsos, P.: Interactive architectural design with diverse solution exploration, IEEE Transactions on Visualization and Computer Graphics, 27(1), 2019, 111-124. https://doi.org/10.1109/TVCG.2019.2938961

[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] Chen, L.; Zhan, W.; Tian, W.; He, Y.; Zou, Q.: Deep integration: A multi-label architecture for road scene recognition, IEEE Transactions on Image Processing, 28(10), 2019, 4883-4898. https://doi.org/10.1109/TIP.2019.2913079

[4] Croce, V.; Caroti, G.; De Luca, L.; Jacquot, K.; Piemonte, A.; Véron, P.: From the semantic point cloud to heritage-building information modeling: A semiautomatic approach exploiting machine learning, Remote Sensing, 13(3), 2021, 461. https://doi.org/10.3390/rs13030461

[5] Dounas, T.; Lombardi, D.; Jabi, W.: Framework for decentralized architectural design BIM and Blockchain integration, International Journal of Architectural Computing, 19(2), 2021, 157-173. https://doi.org/10.77/478077120963376

[6] Han, Y.-S.; Lee, J.; Lee, J.; Lee, W.; Lee, K.: 3D CAD data extraction and conversion for application of augmented/virtual reality to the construction of ships and offshore structure,

International Journal of Computer Integrated Manufacturing, 32(7), 2019, 658-668. https://doi.org/10.1080/0951192X.2019.1599440
[7] Hu, L.; Nie, Y.; Zhang, J.; Zhang, S.: GMC_FM: a grid and multi-density-based method for matching ancient Chinese architectural images, Machine Vision and Applications, 33(2), 2022, 25. https://doi.org/10.1007/s00138-022-01274-1
[8] Koo, B.; Jung, R.; Yu, Y.; Kim, I.: A geometric deep learning approach for checking element-to-entity mappings in infrastructure building information models, Journal of Computational Design and Engineering, 8(1), 2021, 239-250. https://doi.org/10.1093/jcde/qwaa075
[9] 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
[10] Lin, C.-J.: Topological vision: applying an algorithmic framework for developing topological algorithm of architectural concept design, Computer-Aided Design and Applications, 16(3), 2019, 583-592. https://doi.org/10.14733/cadaps.2019.583-592
[11] 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
[12] Ma, K.; Mao, Z.; He, D.: Design a network architectural teaching system by auto CAD, Computer-Aided Design and Applications, 17(S2), 2020, 1-10. https://doi.org/10.14733/cadaps.2020.S2.1-10
[13] Pepe, M.; Costantino, D.; Alfio, V.-S.; Vozza, G.; Cartellino, E.: A novel method based on deep learning, GIS and geomatics software for building a 3D city model from VHR satellite stereo imagery, ISPRS International Journal of Geo-Information, 10(10), 2021, 697. https://doi.org/10.3390/ijgi10100697
[14] Zhang, S.; Chen, S.; Zhang, J.; Cai, Z.; Hu, L.: Image annotation of ancient Chinese architecture based on visual attention mechanism and GCN, Multimedia Tools and Applications, 81(28), 2022, 39963-39980. https://doi.org/10.1007/s11042-022-12618-4
[15] Zhen, L.-I.; Dan, H.-U.; Zhao, Y.: Effect of architectural 3D morphology on atmosphere-soil energy processes/air temperature/relative humidity, Acta Ecologica Sinica, 42(6), 2022, 2175-2185. https://doi.org/10.1016/j.uclim.2022.101324