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Application of Machine Learning in Architectural Design-a Review

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ABSTRACT: This paper first clarifies the two popular concepts of "machine learning" and "neural network," combs the current cutting-edge research in the field of architectural design, then introduces the interface tools needed from the perspective of architectural design practice, and looks forward to the trend of application in the future.

KEY WORDS: machine learning; neural network; architectural design; cutting-edge research

Currently, neural network deep learning technology is widely used in fields such as image recognition and recommendation algorithms, and related concepts like machine learning, neural networks, and artificial intelligence are becoming increasingly well-known to the public [1]. What are the specific applications of machine learning and neural network technology in the field of architecture? How do these cutting-edge technologies intervene in the architectural design process? These have become issues of concern to many architectural scholars.

The concepts of machine learning and neural networks are relatedbut have different focuses, which have led to confusion and misunderstandings. Most architects still cannot grasp the essence of neural networks and machine learning. This paper uses knowledge graphs to sort out the current international research status in architecture and related fields, analyzes the potential and limitations of using such tools in architectural design, and sorts out the cutting-edge research results of machine learning for architects and architectural design stages, exploring its potential to intervene in future architectural design processes.

1 Concept and classification of machine learning and neural networks

1.1 Concept and classification of machine learning

Machine learning is an interdisciplinary subject involving probability theory, statistics, convex analysis and other disciplines. It acquires new knowledge from data, improves its own performance based on this knowledge "experience" to make effective decisions in new situations, and simulates human learning behavior to a certain extent. Since the early 1950s, two schools of thought have emerged: "symbolism" based on logical representation and "connectionism" based on neural networks. The "statistical learning" idea represented by support

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vector machines (SVM) and kernel methods, which appeared in the 1990s, provides effective algorithmic tools for contemporary machine learning applications [2]. For different machine learning tasks, algorithm engineers use different "machine learning algorithms" - such as support vector machine (SVM) algorithm, k-nearest neighbor (KNN) algorithm, decision tree algorithm, etc.for classifying labeled data[1]; LASSO algorithm for regression prediction of labeled data; K-means algorithm for clustering analysis of unlabeled data, principal component analysis (PCA) algorithm for dimensionality reduction analysis of high-dimensional data that explores intrinsic correlation, etc. [3] (Figure 1).

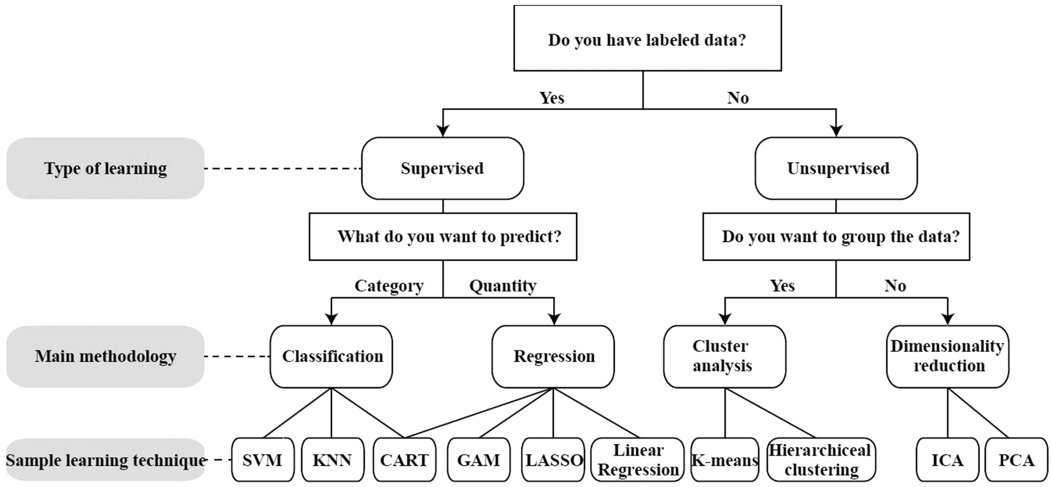

Figure 1 Types of machine learning and corresponding representative algorithms

1.2 Concept of neural network

Neural network in the field of machine learning refers to "neural network learning," which describes the core design idea of a class of tools to achieve the aforementioned machine learning tasks - building a neuron model inspired by biological neural networks to achieve machine learning tasks [2]. A neural network is a widely parallel interconnected network composed of simple adaptive units. Its organization can simulate the interactive response of biological nervous systems to real-world objects [4].

The most basic component of a neural network is a neuron. The signals transmitted by other neurons are transmitted to a certain neuron through weighted connections. The total input of these signals is processed by the activation function and then transmitted to other neurons. Many such neurons are connected according to a certain structure to form different types of neural networks. Generally, the use of neural networks is divided into two stages: training and prediction - in the training stage, known data is input, and the weight value of each neuron is updated through the back propagation algorithm. In the prediction stage, the data to be predicted is input, and the classification, regression, clustering and other prediction results of the new data are calculated using the neural network model after the weight value is updated (Figure 2) [2]. However, theconnectionist nature of neural network determines that its internal computing mechanism cannot be clearly explained, making it a "black box" tool.

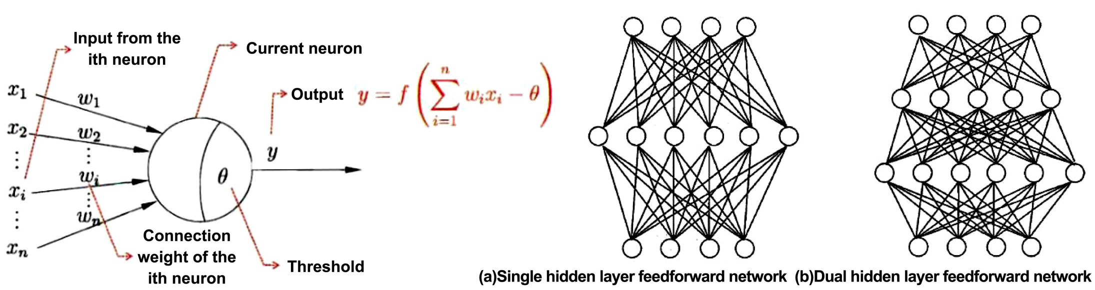

Figure 2 Schematic diagram of the basic principle of feedforward neural network

2 Research based on literature analysis

CiteSpace is a tool for literature analysis based on the principle of knowledge graph. By analyzing the citation relationship characteristics and keyword frequency of different documents, it can explore the research hotspots and research trends in a certain discipline [5]. In a broad sense, architectural engineering design includes architectural design, building structure, HVAC system, construction management and other fields. As "architecture," architectural design-related research is more exploratory and applied because it is more practical. At present, in the field of architectural engineering, the mainstream research of machine learning focuses on air conditioning and energy consumption, building structure, and construction engineering management, as it is suitable for data prediction and feature analysis tasks in complex multivariate scenarios.

The Scopus database was used to analyze the literature of cutting-edge international academic conferences in the field of architectural design, and a total of 123 research documents from 1999 to 2019 were obtained. Since the number of citations of international conference papers is very small compared to journal papers, it is impossible to conduct effective literature co-citation analysis. The keyword analysis function in CiteSpace is used to explore the potential application hotspots of machine learning in the field of architectural design. Noun keywords form a word cloud,where the size of the keyword indicates the number of times it appear and the distribution of keywords reflects the concentration of research hotspots, as shown in the following figure (Figure 3).

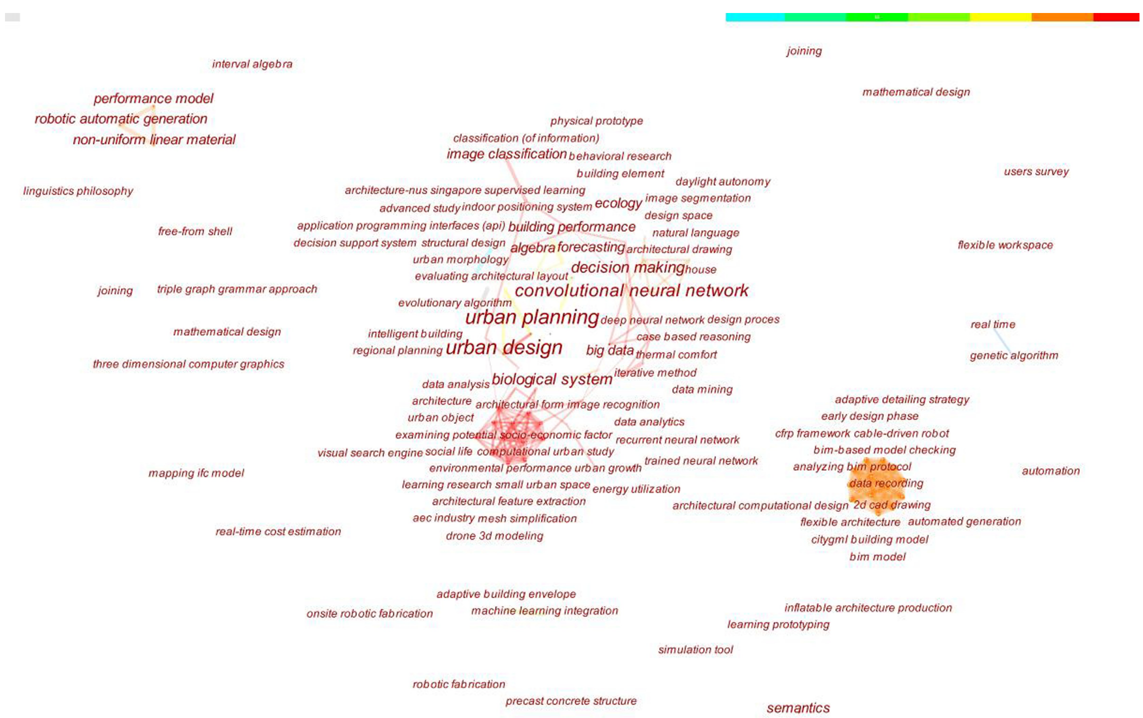

Figure 3 Potential application hotspots of machine learning in architectural design

The following conclusions can be drawn from the visualization results:

(1) Urban design/urban planning related issues are mentioned frequently, and related keywords form a certain degree of concentration, with diversified research directions, including environmental performance, architectural feature extraction, social life, etc.

(2) Keywords such as building performance/performance model, robotic automatic generation, image classification, decision making, and no-uniform linear material have a high frequency of occurrence, representing the current hot research directions.

(3) Therange of other keywords is quite wide, and the distribution is relatively even, including architectural layout, free-form shell, BIM-based model check, evolutionary algorithm, data mining, real-time cost estimation, and many other different research directions, which represent the current academic exploration and practice in various

subdivided research directions.

It is worth noting that, since machine learning is still an emerging technology, its application in the field of architectural design is still in its infancy, and the number of related studies is not large. Since keyword analysis of a small number of documents cannot guarantee a clear and accurate research context, this article will obtain a more in-depth research status through manual screening of the latest international conference papers.

3 Research on cutting-edge applications of machine learning for architectural design

In order to solve the lag of Scopus and other databases in collecting cutting-edge literature from international conferences, the latest research literature in the field of architecture was manually retrieved (including important international conferences and related journal papers in the past three years as of June 2020) to show the cutting-edge application of machine learning technology in fields related to architectural design. According to the algorithm architecture and research field focus, all the literature can be divided into 12 major algorithm categories andeight research directions. All the above literature is presented in a table as shown in the following table (Table 1).

According to the complexity of the machine learning algorithm, all the machine learning algorithms involved are divided into non-deep learning algorithms and deep learning algorithms. In addition to the traditionalsimple artificial neural network (ANN) algorithm, non-deep learning algorithms also include regression analysis, SVM, SOM algorithm, etc., which are widely used in other construction engineering fields besides architectural design. Deep learning algorithms involve multiple layers of complex neural networks, including the more popular CNN, GAN, RNN algorithms and style transfer algorithms, graph-based algorithms, reinforcement learning algorithms, etc. Deep learning algorithms have better recognition capabilities for high-dimensional data and abstract features.

3.1 Analysis of cutting-edge applications from the perspective of algorithms

The application of traditional non-deep learning algorithms (excluding Simple ANN shallow neural networks) is concentrated in research areas such asarchitectural form, building performance and user behavior. Although these machine learning algorithms have been maturely applied in engineering fields such as structure and HVAC, they have not been widely mentioned in cutting-edge research in the field of architectural design. Among them, the SOM self-organizing neural network maps high-dimensional data to a two-dimensional grid and performs self-organizing clustering. It can be used to refine building forms [15][16], judge the correlation between a large number of morphological control parameters of complex structures and the final construction results [21], analyze the complex correlation between environmental factors and various physiological indicators of users [17] (Figure 4), and can also be creatively applied to CFD fitting calculations of building wind environment [18], showing great potential for future applications. Nathan Brown et al. applied the PCA principal component analysis method to the optimization process of large-span truss structures, integrating the height parameters of the truss control points and abstracting them into several control variables with different weights that affect the performance of the truss structure, ensuring that architects can have further room for free form adjustment while intuitively grasping the performance of the building structure [7] (Figure 5). It is worth noting that all applications above involve research related to building performance to coordinate complex nonlinear parameter relationships.

Machine learning algorithms represented by Simple ANN learn the corresponding input-output association patterns from multivariate high-dimensional data sets, thereby establishing an input-output association model. By inputting new data into the trained prediction model, the corresponding data output can be predicted. This property is widely used in the field of building energy consumption prediction to accelerate the speed of building energy consumptionoptimization and is called the "surrogate model" or "metamodel" method (surrogate model/metamodel) [80][81][30][31][32] (Figure 6). Similarly, the metamodel method can be used in the direction of structural performance optimization, such as assisting designers in judging the performance trend of the entire scheme search space

Table 1 Literature review on cutting-edge applications of machine learning for architectural design

		Feature recognition	Plane topology generation and optimization	Robotic arm construction process	Urban form	Architectural form	Structural optimization	User behavior analysis	Building performance
Non-deep learning	Traditional regression algorithm								[6]
	PCA analysis					[7] [8]			
	SVM								[9]
	KNN/K-means	[10]			[11]	[12] [13]		[14]	
	SOM					[15] [16]		[17]	[18]
	Simple ANN			[19] [20] [21]	[22]	[23] [8] [24] [25]	[26] [27] [28]	[29]	[30] [31] [32] [33] [34] [35]
Deep learning	CNN	[36] [37] [38] [39] [40] [41] [42] [43]		[44]	[45] [46]	[47] [48]		[14]	[49]
	GAN	[50] [51] [52]	[53] [54] [55]	[56] [57]	[58]	[59] [60]			[61] [62]
	RNN		[63]	[64] [65]				[66] [67]	
	Style transfer				[68]	[69] [70] [71] [72] [73] [74]			
	Machine learning algorithm based on graph structures		[75] [76] [77] [63]						
	Reinforcement learning				[78]		[79]		

during the optimization process [26], accelerating structural static optimization calculations [27], and quickly predicting structural performance involving more material property settings [28]. Compared with the aforementioned machine learning algorithms, simple ANN can more effectively capture the inherent correlation of complex parameter constraints and have a wider range of applications. It can fit the morphological changes of architectural forms as the control points move [23], proving its ability to effectively capture nonlinear complex parameter relationships for interpolation calculations, which can also be applied to the optimization of robot arm operation paths [19][20]. Wang Zhenyu et al. used the surrounding urban environment data of 440 built museums in China (the number and location of bus stops, surrounding road grades, etc.) and the location of the main entrance of the museum as input and output to train a single hidden layer neural network. The neural network can decide the best entrance location of the museum based on the new given museum site selection environment, and the consistency rate is 70%-90% compared with manual selection [22]. Christian Theoborg [8] (Figure 7) and Zheng Hao [24] used morphological parameters as the input of the neural network and the observer's score of morphological beauty as the output of the neural network, thereby "mimicking" people's subjective preferences to assist the process of architectural form optimization. The above two types of applications can be regarded as fitting the human decision-making process, which is a relatively basic form of "artificial intelligence."

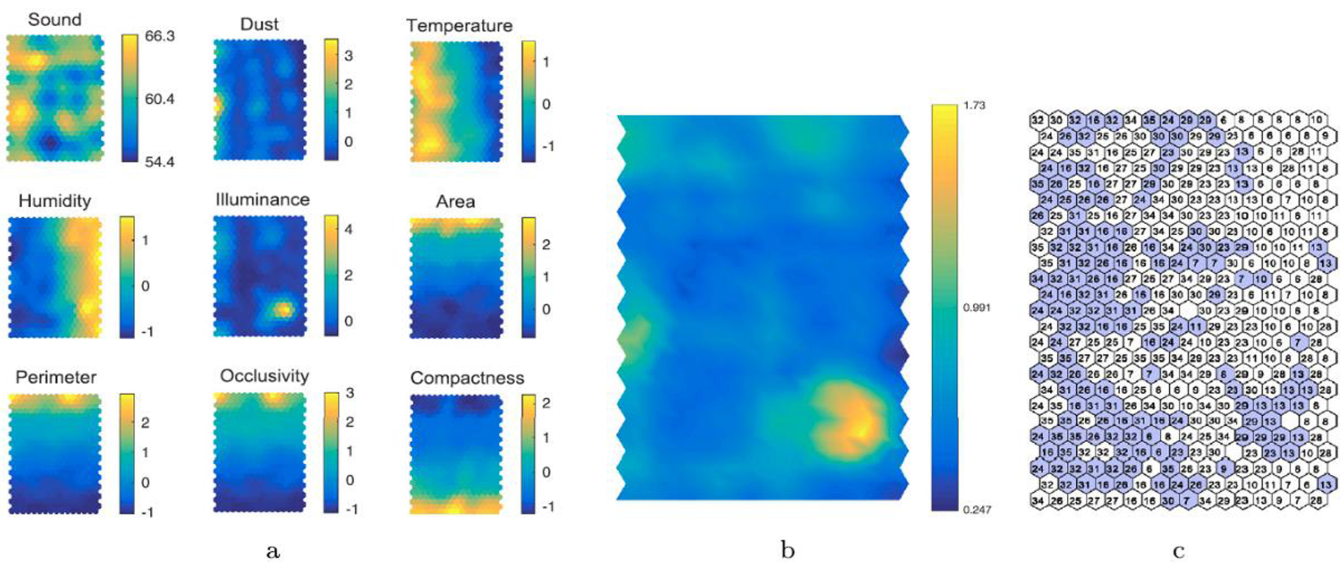

Figure 4 Using SOM neural network to explore the correlation between different environmental data and human physiological response indicators

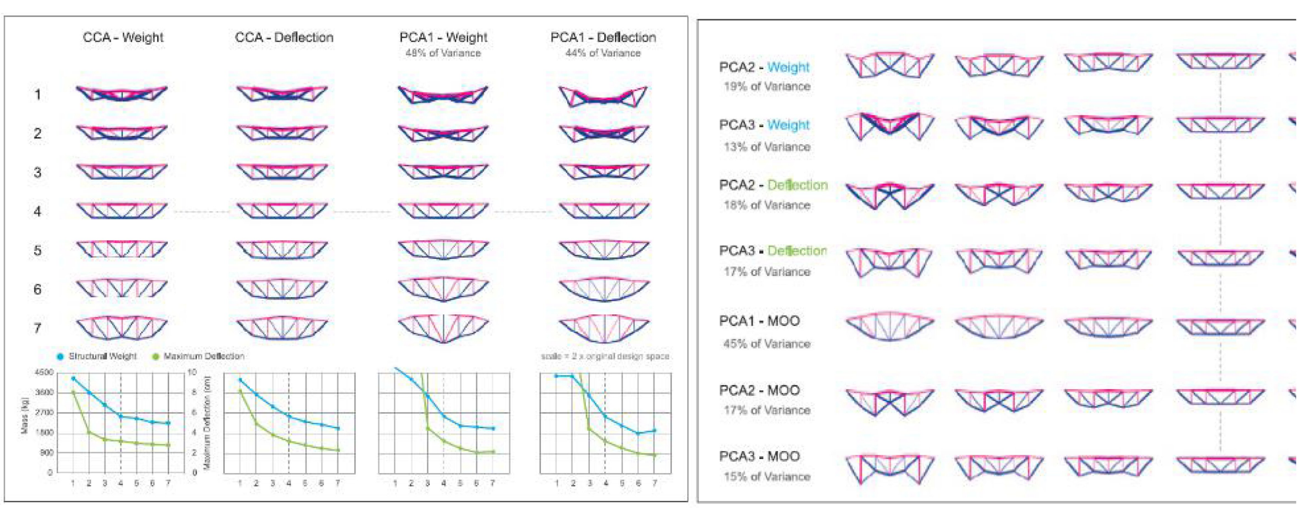

Figure 5 Effects of different weights obtained by principal component analysis (PCA) and canonical correlation analysis (CCA) algorithms on truss shape and performance

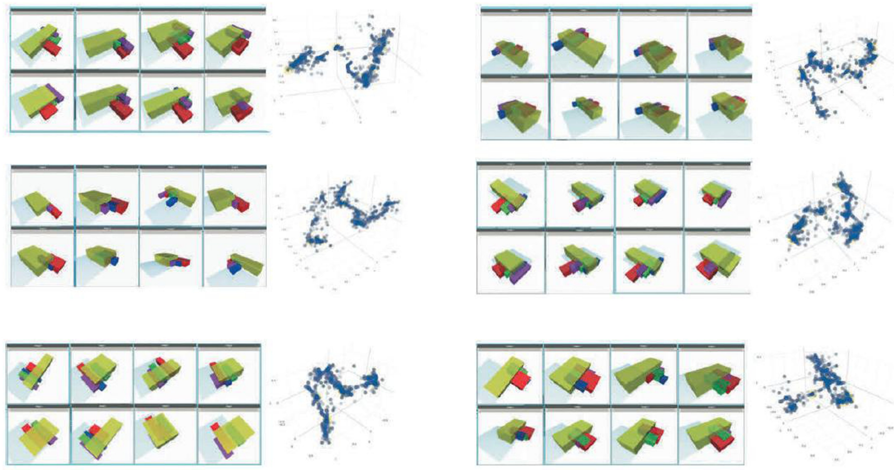

Figure 6 Machine learning-based “surrogate model”/“meta-model” approach to assist building performance optimization

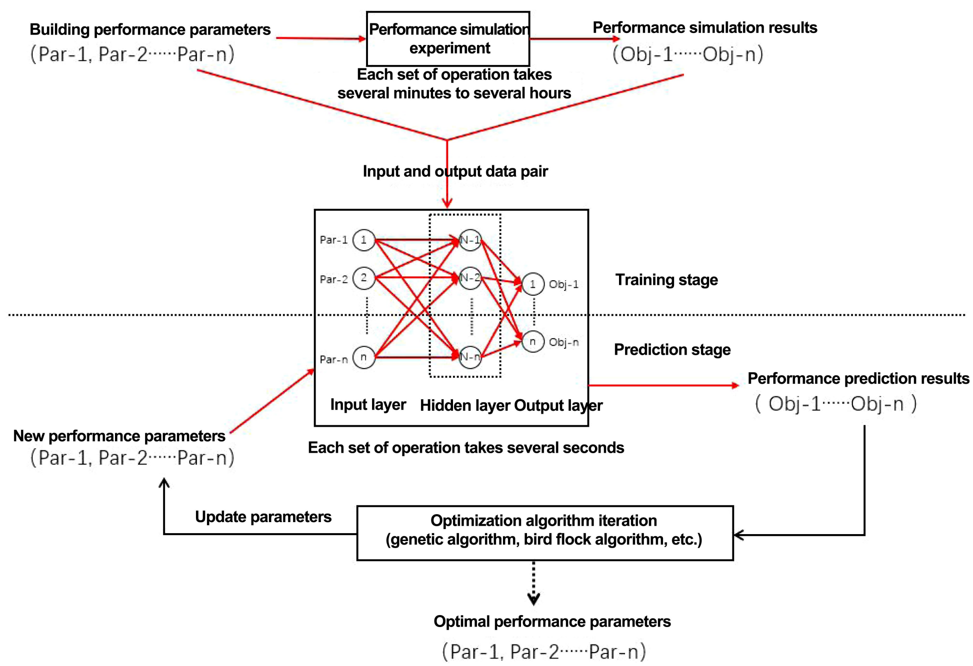

Figure 7 Neural network simulation of architects' preference of forms and PCA cluster analysis results

Convolutional neural network (CNN) has become an important tool in the field of image feature recognition due to its ability to interpret abstract features of two-dimensional images. Yuji Yoshimuraet al. input images of works by architects of different styles into a deep convolutional neural network for training, resulting in a CNN that can identify abstract architectural style features from the newly input architectural images, infer which architect the style of the building belongs to, and mark which areas of the architectural image the inference is based on in the form of a pseudo-color image [36] (Figure 8). This is the most intuitive application of two-dimensional image recognition technology in the field of architectural design. Furthermore, a recommendation system called DANIEL can extract the building layout logic based on the input building plan, and output several building plans with similar features, providing buyers with a variety of candidate options [43] (Figure 9). In addition to performing traditional image recognition and classification tasks [36][37][38][39][40][41][42][44] to assist the architectural design process, CNNs can also automatically identify urban block types at the city scale with the help of satellite images [45], expanding the application of CNNs to the field of urban morphology planning.

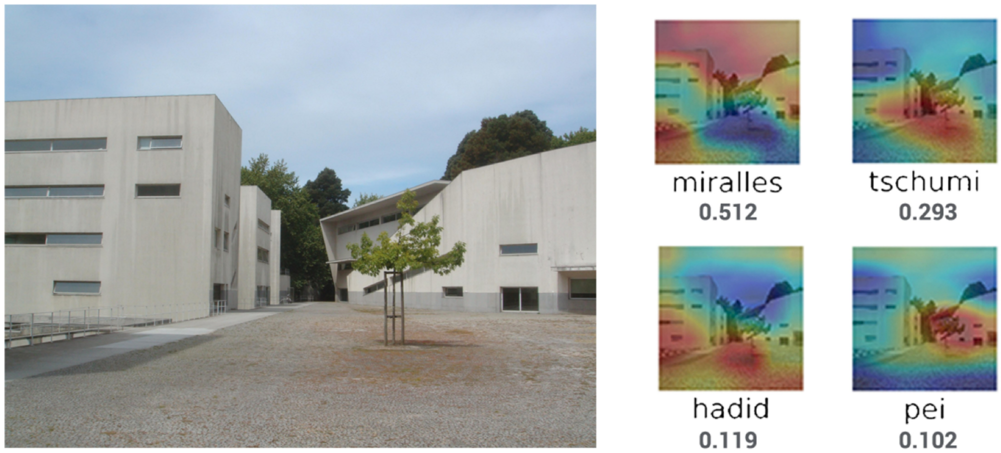

Figure 8 Deep learning neural network recognizing architectural style

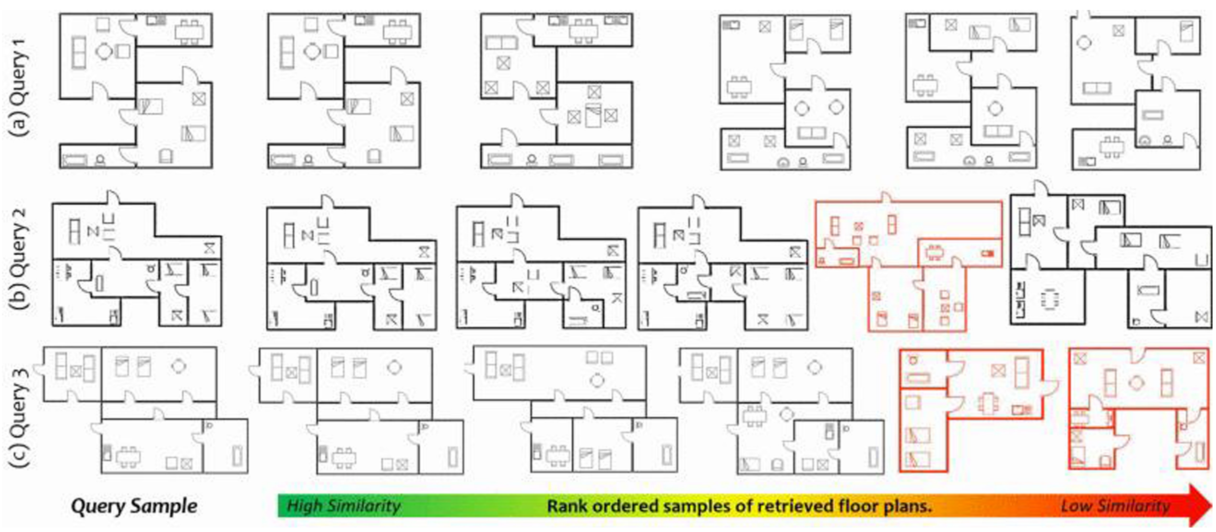

Figure 9 Deep learning neural network recommendation system generating similar candidate solutions based on reference plane

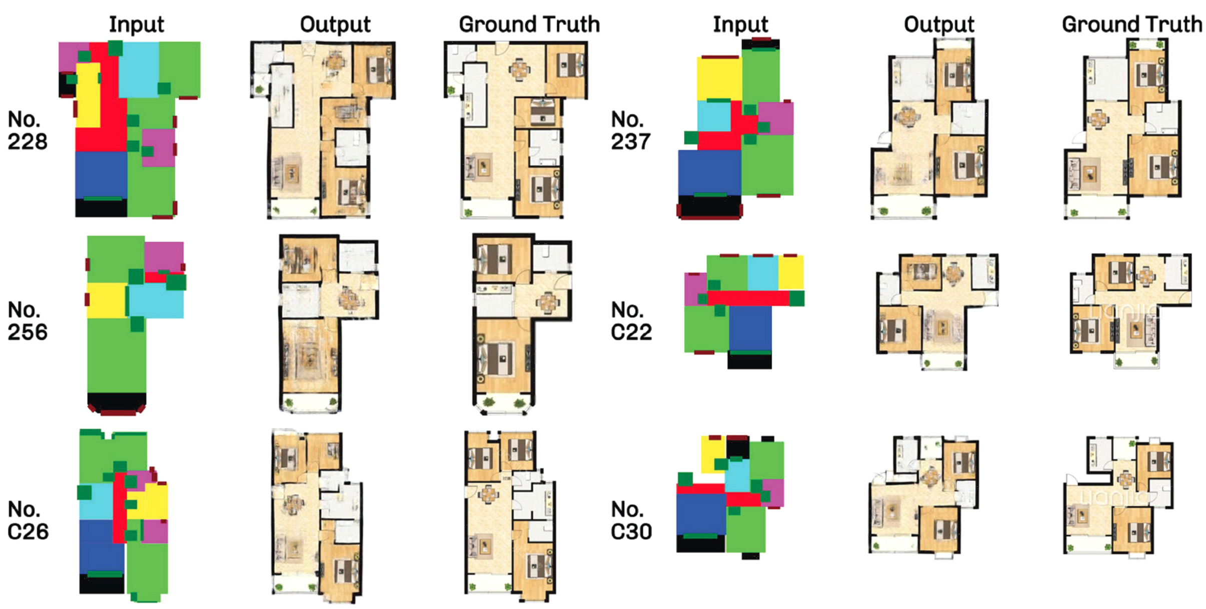

Figure 10 Deep learning neural network generating architectural plan based on functional color block map

The input and output parameters ofa generative adversarial network (GAN) are both two-dimensional image data. Zheng Hao, Huang Weixin et al. obtained 155 residential floor plans from the lianjia.com website and drew corresponding functional color block diagrams to mark room functions with different colors, which were connected to the pix2pixHD neural network [82] as the output and input ends for training. The trained neural network can generate realistic floor plans based on the newly input functional color block diagram [53] (Figure 10), which proves the feasibility of using the architectural floor plan as a two-dimensional image for information exchange. Stanislas Chaillou made a further attempt at plane generation on this basis, using the GAN to simulate the entire floor plan design process of building red line-building base outline-room division-door and window opening design-furniture arrangement. A large number of alternative options can be generated for each step. Relying on the real-time tree selection interface, designers can flexibly filter the generated results of each step [55] (Figure 11). On the other hand, the research using scene photos as a medium also shows the potential value GANs: the domestic Xiaoku team launched the "Rosetta Project" in 2017, using the styleGAN neural network to conduct in-depth learning of a large number of existing excellent architectural design cases, establish a huge knowledge base on design style, logic and concepts, and output the learned intelligent design results for designers to refer to [59] (Figure 12). The GAN Loci study by Steinfeld et al. compared the potential of Pix2pixHD and styleGAN neural networks to reproduce the "Genius Loci" of different cities, demonstrating the powerful recognition and induction ability of GAN neural networks for abstract features [58] (Figure 13).

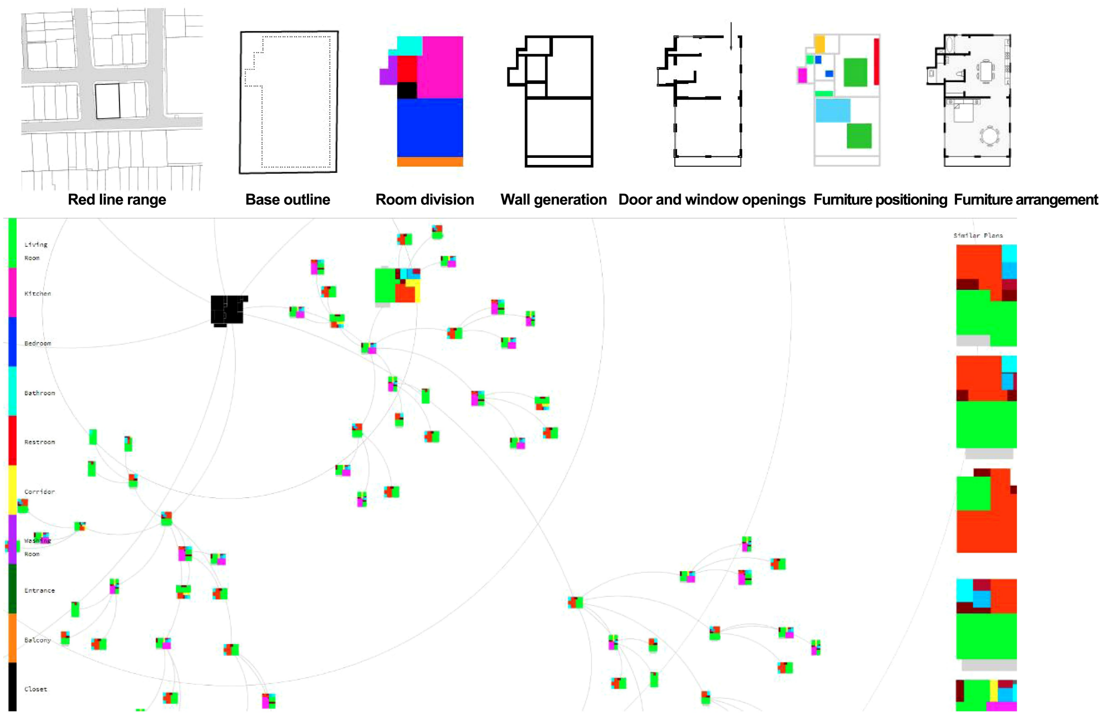

Figure 11 Architectural plan design process and tree-like scheme screening interface based on generative adversarial network (GAN)

Compared with CNN, recurrent neural network (RNN) can flexibly process data sequences of different lengths, so it is used in fields such as text and speech semantic analysis. This allows it to not only simulate crowd behavior based on time seriesdata [66], but also identify the topological similarity of architectural planes [63] and predict the deformation characteristics of inhomogeneous materials in combination with graph structure [2)]. Furthermore, if the architectural design steps are regarded as time series data to train RNN neural networks, it can understand the nonlinear design decision process and assist architects in making decisions [67].

Style transfer technology for two-dimensional images, graph structures used for social data processing, and reinforcement learning algorithms have found their place in research directions such as assisting designers in obtaining creativeinspiration [68][69][70][71][72][73], identifying architectural space topological relationships [75][76][77], generative design based on dynamic feedback [78] and structural optimization methods [79]. Among them, Professor Sun Cheng's team applied style transfer technology to three-dimensional architectural forms to assist in the style consideration of three-dimensional architectural forms based on the semantic information of two-dimensional conceptual intention maps, which provided new ideas for future architectural design [74].

Figure 12 Modern style building facade based on styleGAN

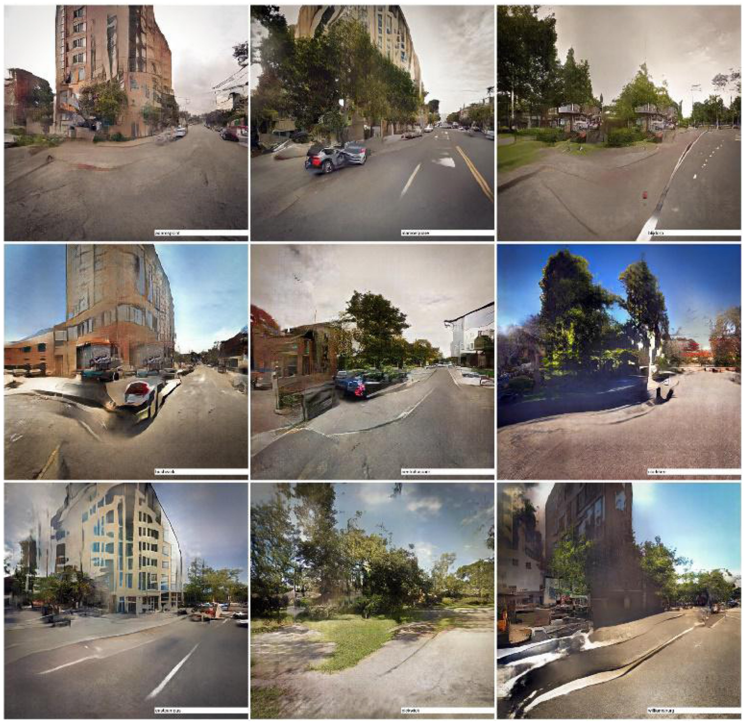

Figure 13 Cityscape image generation based on pix2pixHD

3.2 Analysis of cutting-edge applications based on different research directions

Feature recognition technology has received widespread attention with the recent popularity of CNNs. Feature recognition methods based on CNNs mainly rely on two-dimensional images and are used in different branches of architectural design to help designers improve efficiency. Yuri Kato et al. combined CNN with Google Maps to extract street interface color matching patterns [38] to provide a basis for subsequent architectural and urban planning decisions; KIM, JINSUNG et al. studied how machine learning can help computers automatically identify the types of unknown building components [37].

The application of machine learning at the urban morphology level is also mainly based on pixel processing of urban planning images, and then using algorithms such as CNN, GAN, and Style Transfer to identify abstract features and convert morphological styles based onthem. Peng Qian et al. from Tongji University discussed the current application prospects of artificial intelligence in the field of urban planning and used CNN to perform large-scale and detailed discrimination of urban texture and land use classification [45] (Figure 14).

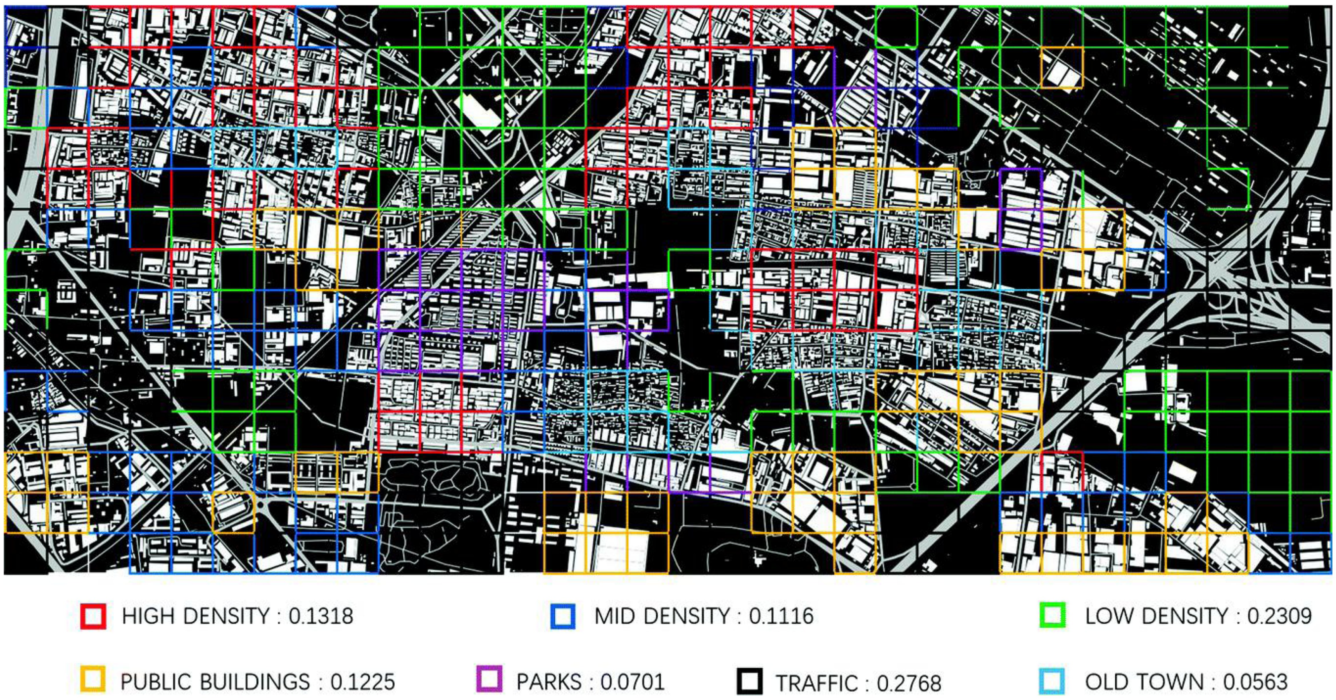

Figure 14 Urban morphology recognition based on CNN neural network

The study of architectural plan and spatial topology hasthe development of two completely different paths. The first is the generative design method based on the GAN network mentioned above. It uses the pixel format image of the architectural plan for training to obtain new plan layout schemes. However, this plan generation method cannot exchange data directly and accurately with vector modeling software. The second machine learning method based on graph structure can more effectively express the topological relationship of architectural space and has greater potential to be integrated into the traditional architectural design process [63][75][76][77] (Figure 15, Figure 16).

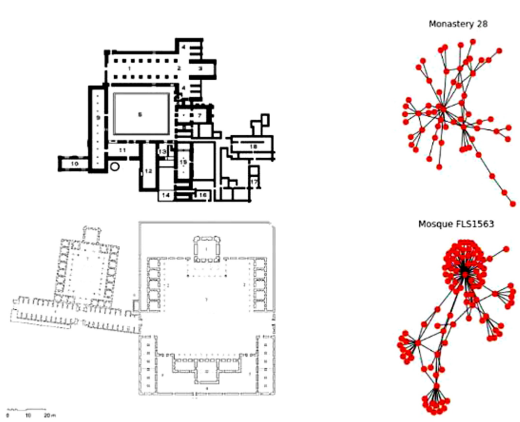

Figure 15 Topological analysis of architectural plan

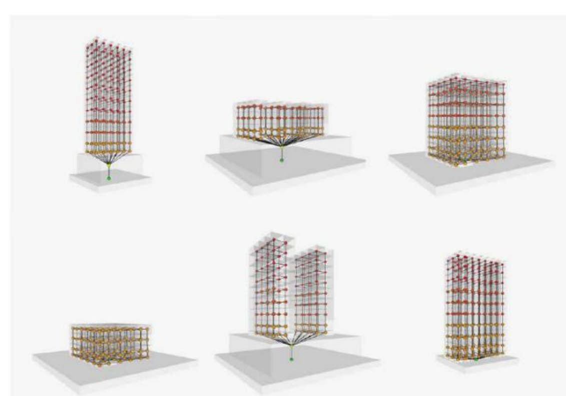

Figure 16 Visualization of spatial organization diagram structure of three-dimensional building

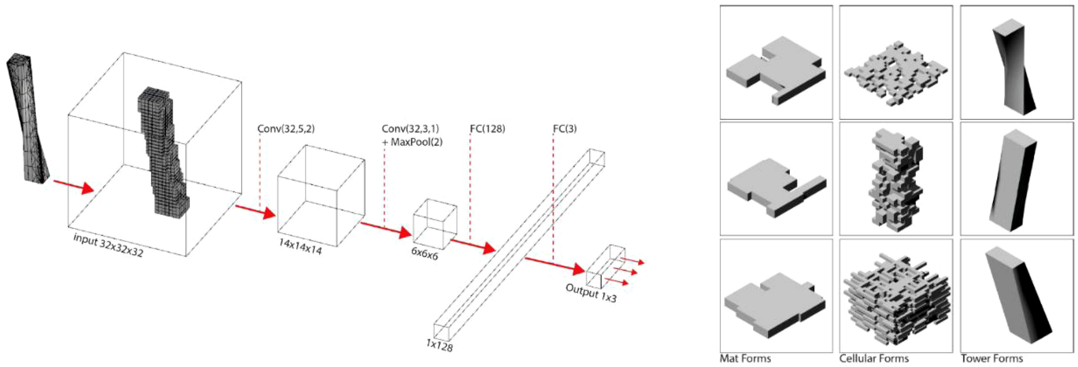

Figure 17 Architectural form translation based on pixelation

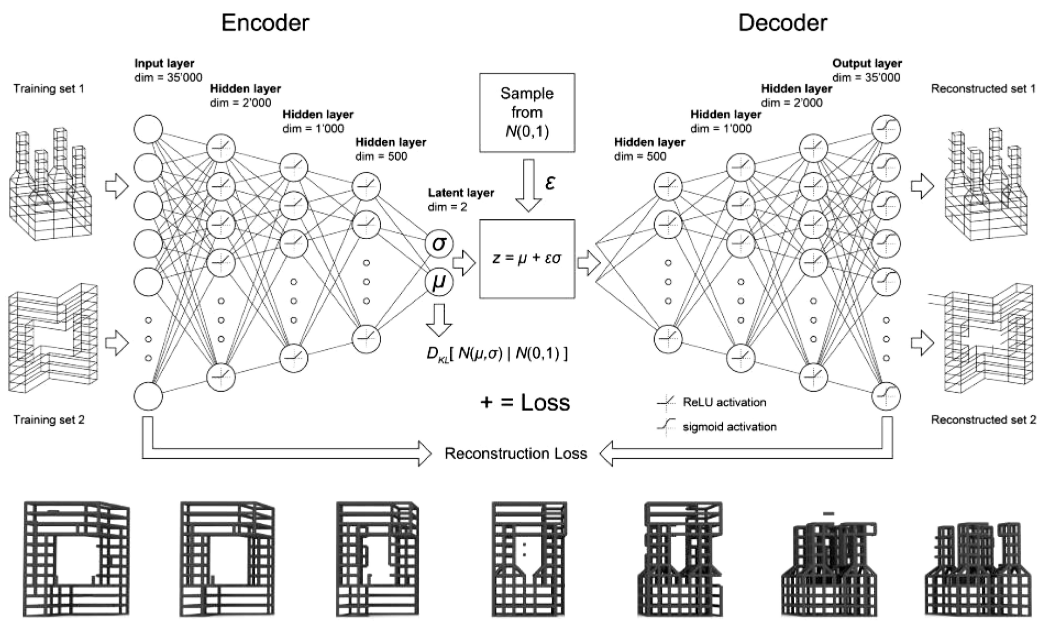

Figure 18 Method of mixing architectural form features based on autoencoder network

At the architectural form level, in addition to extracting the intrinsic correlation between form control parameters and subjective evaluation parameters, another research direction with potential value is how to translate three-dimensional architectural form information for use by machine learning algorithms. By pixelating the three-dimensional form of the building and treating it as three-dimensionally distributed pixel points, a corresponding three-dimensional convolutional neural network (3dCNN) can be created. David Newton established a 3dCNN network by linking the Keras neural network tool on the grasshopper platform, which can currently identify three characteristics of buildings [47] (Figure 17). Jaime de Miguel et al. added neighboring information around each sampled "pixel point" on this basis. The translated architectural form information was input into the autoencoder network and compressed into a vector in a latent space through four hidden layers. By training two different architectural forms, smooth sampling between two corresponding vectors in the latent space can yield a mixed result of the characteristics of the two architectural forms [25] (Figure 18), which is similar to the results of architectural form research based on the SOM algorithm [16] (Figure 19). Steinfeld et al. established an application framework of machine learning in generative design by taking another path to translate the three-dimensional form of buildings: the images of the cut surfaces of the three-dimensional building entities in different directions were used as the input of the neural network to describe the form information, and the GAN neural network was further used to generate new three-dimensional entities, proving the feasibility of this form translation method [60] (Figure 20).

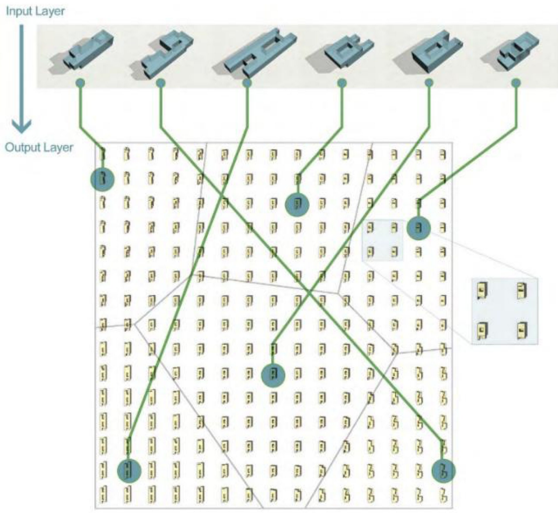

Figure 19 Method of mixing architectural form features based on SOM network

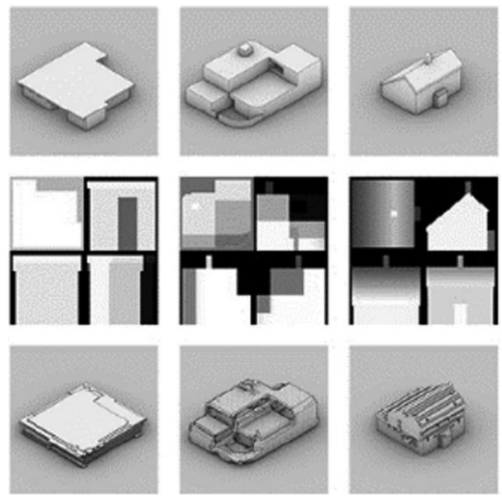

Figure 20 Architectural form translation based on multiple views

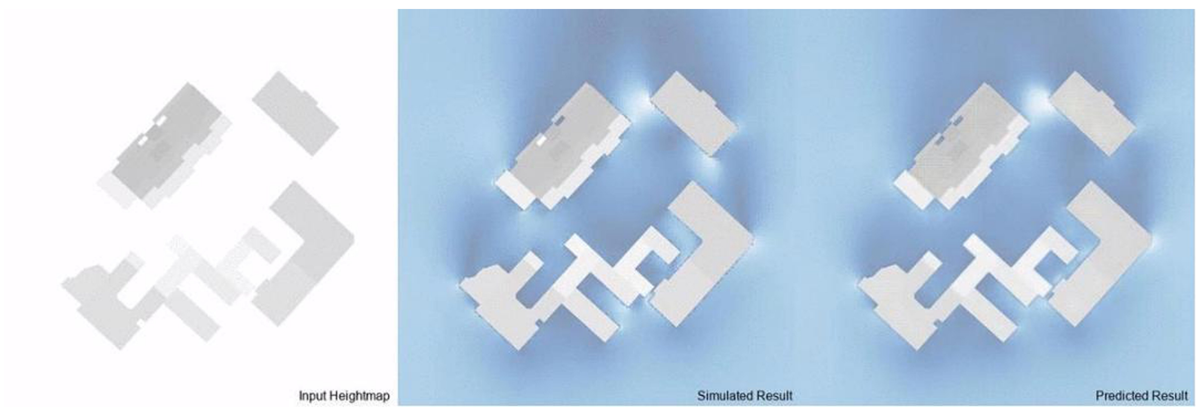

Figure 21 Comparative analysis of real-time building wind environment prediction based on urban elevation grayscale image and traditional simulation results

Machine learning as a pattern recognition tool has shown its potential in the fields of robotic arm construction, structural optimization, user behavior analysis, and building performance analysis and optimization. Among them, Angelos Chroniset al. used GAN neural networks to establish a real-time modeling visualization platform based on Rhinoceros3D, focusing on solving the environmental performance simulation at the urban scale. The input data of the neural network is a grayscale image expressing the building elevation, and the real-time output data is a pseudo-color map of wind pressure and solar radiation at pedestrian height, which is sufficient to assist architects in intuitively perceiving the impact of building layout on the urban wind and heat environment (Figures 21 and 22) so as to optimize the urban form more comprehensively [62]. The algorithm is integrated into the latest Giraffe urban design platform as a toolkit for calculating the comfort of the ground wind environment. Its rapid performance feedback has aroused widespread discussion in the architectural community [3)]. The SOM algorithm also has applications in this regard. Relying on Mathematica numerical calculation of the SOM neural network for CFD fitting, three-dimensional wind field data is quickly generated [18]. Thomas Wortmann and other scholars developed a meta-heuristic optimization algorithm based on the meta-model idea, and based on this, developed an optimization plug-in Opossum in the Grasshopper platform. Compared with traditional optimization algorithms such as genetic algorithms, this optimization algorithm can obtain better performance optimization results with a smaller number of iterations [35].

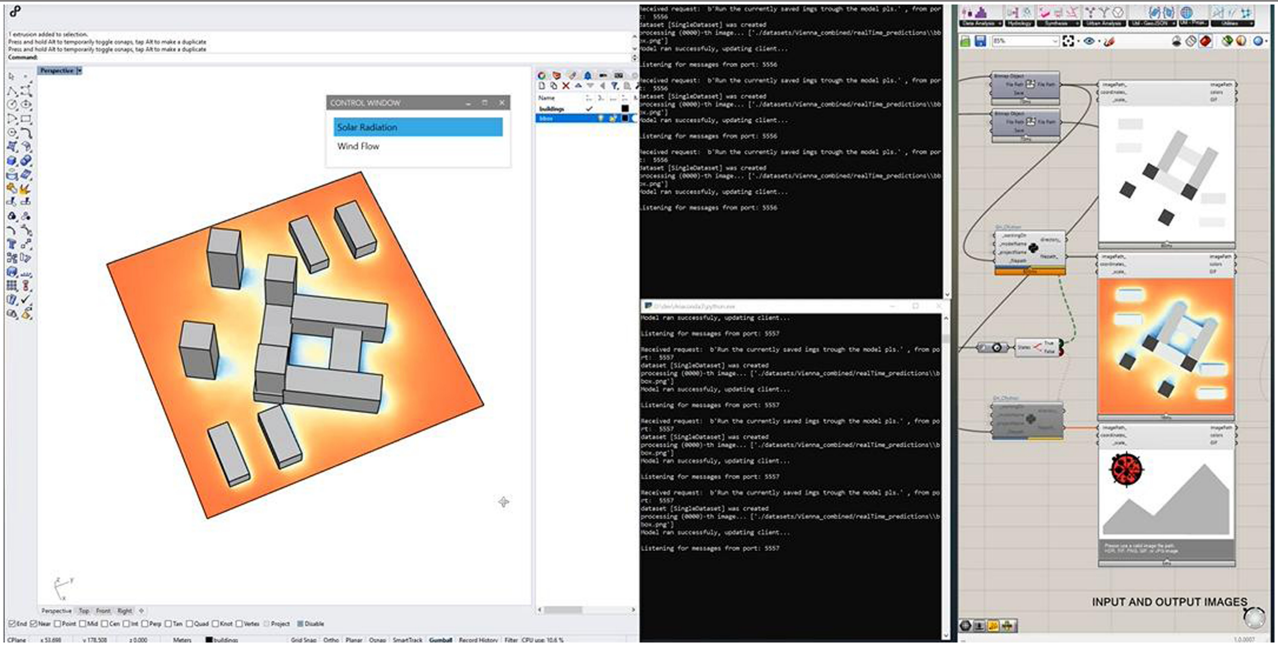

Figure 22 Real-time building sunlight effect prediction results based on the city elevation grayscale image - system interface based on Rhinoceros3D+grasshopper

4 Application path of machine learning methods

Currently, the research and application of machine learning for architects are still in their infancy. This section introduces the machine learning tools and interfaces that architects can use at this stage, as well as the corresponding typical application paths.

4.1 Machine Learning Toolkits and Software

Currently, there are various mature machine learning algorithm toolkits with different focuses. Toolkits such as Accord.NET Framework, NeuronDotNet.dll, AForge.Neuro.dll/NLOptDotNet.dll are lightweight .NET-based machine learning algorithm packages. When writing plug-ins, the corresponding .dll files can be directly called to implement machine learning algorithms. However, these tools cannot complete complex machine learning tasks such as deep learning, nor can they call GPUs for high-load machine learning calculations. Python, as a "glue language"[4)] is favored by machine learning engineers. Scikit-learn, as a general machine learning algorithm framework in the python environment, provides a large number of modular solutions for executing machine learning algorithms for data mining and analysis, covering almost all mainstream machine learning algorithms, but it is not optimized for the current popular deep learning technologies. Currently, the widely used frameworks in the field of deep learning are Keras, tensorflow, pytorch, Caffe, etc., which can flexibly build customized deep learning neural networks through python interfaces. At present, most deep learning-related research is based on the above deep learning frameworks. MATLAB, as a widely used software in the engineering field, also includes a machine learning module. The MATLAB API can realize real-time data transmission between MATLAB and external engineering design software.

4.2 Implementation of machine learning without 3D modeling software

The current mainstream machine learning research focuses on the processing of big data media materials such as images and texts. Directly using such media materials to solve relevant problems in the field of architecture does not require the participation of 3D modeling software. For example, in the relevant research of scholars such as Zheng Hao [53] andSteinfeld [58], floor plans and street view pictures are used as input and output media, and classic styleGAN, Pix2PixHD and other two-dimensional image-based machine learning algorithm packages are used to generate the required two-dimensional image results. The entire process is directly implemented using the Python programming platform.

4.3 Implementation of machine learning based on 3D modeling software

There are two main paths to implement machine learning algorithms based on 3D modeling software: plug-in tools provided by the modeling software; data exchange between 3D software and mature algorithm platforms.

The plug-in tools provided by the softwareinclude the machine learning algorithm, which does not require designers to perform custom programming, so machine learning algorithms can be quickly integrated into the design process. There are several third-party algorithm grasshopper plug-ins under the Rhinoceros3D platform that support the implementation of machine learning algorithms: opossum optimization plug-in [83] [84], Lunchbox, Owl, Crow, Dodo, ANT plug-in, etc. (Table 2) (Figure 23). Due to the limitations of the software platform, the above plug-ins cannot be linked to GPU for parallel computing, and the setting and modification of their parameters are limited, and the adjustment of these parameters is often the most important issue in neural network design [85]. The Lunchbox plug-in also has a Dynamo platform version based on Revit, which includes the same machine learning algorithm as the grasshopper platform.

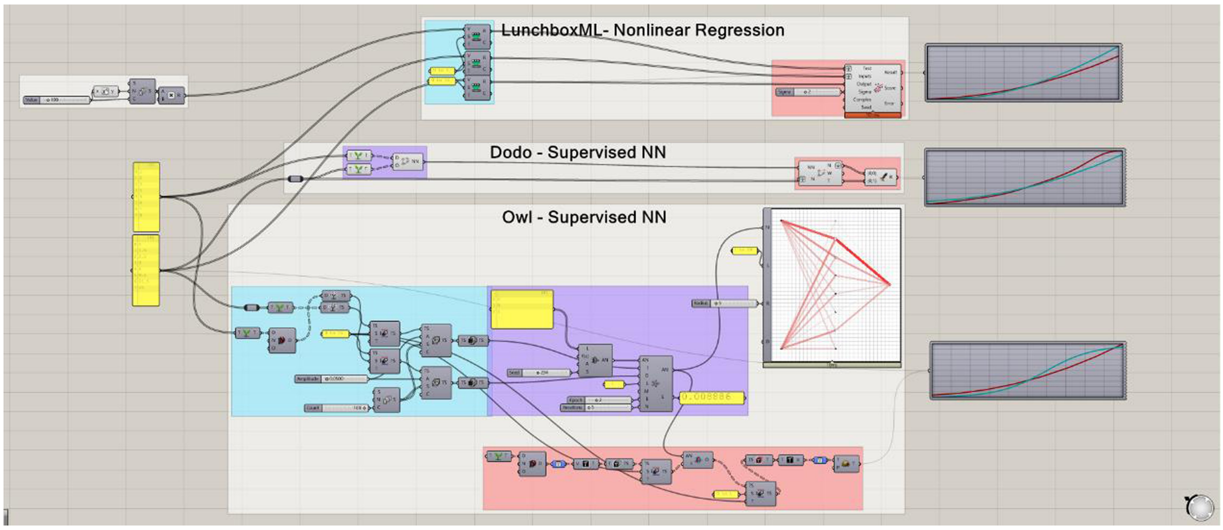

Figure 23 Single-layer neural networks built using LunchboxML, Dodo, and Owl plugins

Table 2 Grasshopper plugins that support machine learning algorithms

Grasshopper plug-in	Relevantarithmetic libraries	Details of machine learning implementation
Opossum	RBFOpt	Implementing a single-objectiveoptimization algorithm based on the "surrogate model" using the RBF neural network.
Lunchbox	Accord.NET Framework	Solves regression problems, clustering-related problems, and builds neural networks; each algorithm is packaged into different operators, which is easy to use, but the algorithm parameters cannot be adjusted in detail (for example, the neural network operator defaults to a single hidden layer network, and it is impossible to write a multi-hidden layer network).
Owl	Accord.NET Framework	Based on the neural network design of visual programming, it can perform tasks such as two-dimensional image recognition, reinforcement learning, and cluster analysis. The construction of the algorithm program requires a certain background knowledge of neural networks.
Crow	NeuronDotNet.dll	Simple forward pass neural network construction (currently only supports classification prediction problems) and SOM self-organizing neural network construction.
Dodo	AForge.Neuro.dll/ NLOptDotNet.dll	Can realize simple forward pass neuralnetwork but does not support discrete data classification problems.
ANT	Scikit-learn	Implements SVM, regression analysis and other functions, and the functions are relatively comprehensive.

There are two ways to exchange data between 3D software and external machine learning tools: through plug-in communication and through file exchange. In the Rhinoceros3D platform, the Ghcpython and ghpython remote plug-ins can directly call machine learning related computing libraries such as numpy, scipy, keras, tensorflow, etc. in the grasshopper interface, which is convenient for establishing a seamless machine learning process; in Revit's Dynamo platform, Python and C# programming languagescan be used to achieve the above data exchange. The PDG parametric platform in Houdini is based on Python language and can also link to classic machine learning algorithm libraries such as tensorflow and pytorch, and its official website introduces a fast terrain generation method based on machine learning [86]. In addition, exporting the data in the 3D software in .csv and other formats is also convenient for calling on Python platforms, MATLAB and other computing simulation platforms, but the storage and reading of exchange files will take a lot of time, which will become a speed bottleneck when processing ultra-large-scale data.

Professor Sun Cheng's team in China proposed a design model for collaborative scheme creation between artificial intelligence andarchitects and used deep learning technology to develop an intelligent design system (Quick Design Generator) that realizes human-machine collaborative scheme design. This system is a typical machine learning implementation method based on 3D modeling software - it converts the three-dimensional architectural data into two-dimensional information in Grasshopper, uses Python language to link the Grasshopper parametric platform with the TensorFlow machine learning framework, combines two-dimensional architectural imagery pictures for style transfer and feeds them back to Grasshopper to generate three-dimensional volumes. This method successfully integrates the architectural design intention features into the three-dimensional architectural volume, assisting designers in scheme creation [74].

5 Conclusion

This paper systematically combs through the cutting-edge research on machine learning and neural network technology in the current field of architecture to represent the application of this advanced technology in the field of architecture as much as possible. Based on the above analysis, we can conclude that the current status and future research trends of machine learning technology in the field of architectural design can be summarized into the following five aspects:

(1) Traditional machine learning tools such as ANN, SVM, and PCA are widely used in the field of architectural engineering. Although they do notboast the "magic" of deep learning technology, they still have great application potential in the field of performance optimization. As shown by the research of Tongji University [33], the use of machine learning technology to couple quantitative building performance indicators with building form characteristics and quickly provide performance feedback is more in line with the needs of increasingly "intelligent" buildings.

(2) Machine learning algorithms based on two-dimensional images (neural network structures such as CNN/GAN) have great potential in expanding the creativity of architects. With the deepening of related research, the intervention of these machine learning algorithms will become more practical. This practicality has been initially revealed in the direction of architectural form creativity [74][73].

(3) How to faithfully translate the three-dimensional information of a building into data that can be "understood" and operated by machine learning is an important research direction. High-fidelity three-dimensional architectural information processing will greatly promote machine learning applications related to architectural form.

(4) Under the premise of using machine learning as an auxiliary tool, different machine learning algorithms can be used in combination throughout the design process to improve designefficiency [21], and different machine

learning algorithms should be screened to obtain the best performance [9][65].

(5) Although the current mainstream 3D modeling platform has introduced a number of machine learning algorithm plug-ins, the current mainstream machine learning algorithm application still relies on classic machine learning algorithm libraries such as tensorflow and pytorch. The method of linking 3D modeling software with machine learning algorithms based on language interfaces such as python willbe the mainstream for a long time.

Architecture is a discipline that combines art and engineering.Therefore, Architects should consider both aesthetic needs and architectural performance requirements. Machine learning and neural network related tools provide architects with the ability to present complex problems from an intuitive data perspective. Its powerful data integration and feature recognition capabilities can also assist architects in rapid and exhaustive solution optimization. These powerful tools can help liberate architects from the boring comparative trial and error, transform the current "labor-intensive" design into "intelligence-intensive" design, and help architects focus more on the intangible elements of architecture, find a better balance between building performance requirements, design aesthetics and social concerns, and expand the boundaries of architecture.

Figure and table sources

Figure 1: Reference [3]

Figure 2: Reference [2]

Figure 3:Drawn by the author

Figure 4: Reference [17]

Figure 5: Reference [7]

Figure 6: Drawn by the author

Figure 7: Reference [8]

Figure 8: Reference [36]

Figure 9: Reference [43]

Figure 10: Reference [53]

Figure 11: Reference [55]

Figure 12: Reference [59]

Figure 13: Reference [58]

Figure 14: Reference [45]

Figure 15: Reference [75]

Figure 16: Reference [76]

Figure 17: Reference [47]

Figure 18: Reference [25]

Figure 19: Reference [16]

Figure 20: Reference [60]

Figure 21: http://cities.ait.ac.at/site/index.php/2019/05/29/wind-flow-prediction-through-machine-learning/

Figure 22: http://cities.ait.ac.at/site/index.php/2019/04/11/solar-radiation-prediction-through-machine-learning/

Figure 23:Drawn by the author

Table 1 and Table 2: Drawn by the author

Notes

1) In supervised learning and semi-supervised learning tasks, the machine learning algorithm receives a set of labeled data during the training phase. The trained machine learning algorithm can guess possible labels based on the newly input unlabeled data. For example, in the training phase of the animal image recognition task, the input labeled data is the image of the animal and the corresponding animal species label. These labeled data usually need to be annotated by humans/experts.

2) Compared with linear structures and tree structures, graph structures are complex nonlinear structures. Graph structures are composed ofvertices and edges. Edges represent the connection between vertices; any two vertices in the graph structure may be connected by edges. Depending on whether the edge is directional, the graph structure is divided into directed graphs and undirected graphs. Graph structures can be used to model many complex systems, such as knowledge graph relationships, social relationships, transportation networks, computer networks, consumer markets, etc.

3) Giraffe is an online urban design platform, official website address: https://www.giraffe.build/

4) Glue language refers to a language that is used to con-

nect various software components to realize the overall business process (handy like glue). It only acts as an intermediate processing module to call various core programs written in other languages and perform comprehensive processing. Python is suitable as a glue language because it has extremely high code readability and flexible syntax as a scripting language, and has a rich third-party library.

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