Automated Structural Design of Shear Wall Residential Buildings Using GAN-Based Machine Learning Algorithm

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Abstract

Artificial intelligence is transforming many industries and reshaping building design processes to be smarter and automated. While a large number of studies on automated building design have been carried out recently, they focused on architectural aspects, leaving a gap in its application to structural design. Considering the increasingly wide application of shear wall systems in high-rise buildings and envisioning the massive benefit of automated structural design, this paper proposes a shear-wall design automation model based on a generative adversarial network (GAN). Its goal is to learn from existing shear wall design documents and then perform structural design intelligently and swiftly. To this end, a database of representative architectural and structural design documents was developed. Then, datasets were prepared via abstraction, semanticization, classification, and parameterization in terms of building height and seismic design category. The GAN model improved its shear wall design proficiency through adversarial training supported by data and hyper-parametric analytics. The performance of the trained GAN model was appraised against the metrics based on the confusion matrix and the intersection-over-union approach. Finally, case studies were conducted to evaluate the applicability, effectiveness, and appropriateness of the innovative GAN-based structural design method.

KEYWORDS: intelligent structural design, shear wall system, generative adversarial network, computer vision, data and hyper-parametric analytics

21 Introduction

22 Intelligent design offers advantages in its ability to minimize manual design work, promote diversity in the
23 design space, and ultimately provide optimal design performance [1-4]. As a result of rapid global urbanization, the
24 demand for high-rise residential buildings is continuously increasing [5-7]. Reinforced concrete shear wall systems
25 have been widely used in high-rise designs. The transfer of architectural proposals to construction documents
26 involves arranging structural layouts, defining the position and orientation of structural systems, and controlling the
27 dimensions of structural components [8]. These steps are fundamental to the design process. However, because of
28 their iterative nature, they are also very time consuming, even when conducted by competent engineers. An
29 innovative design approach with greater efficiency is needed, and the intelligent structural design is an emerging
30 approach.

31 Existing approaches are primarily based on generative design. The commonly used options are as follows: (1)
32 design exploration using topology optimization, genetic algorithms, and cellular automata; (2) design synthesis using
33 generative grammars; and (3) design by analogy [1-4]. These approaches are particularly favorable for geometric
34 modeling and are less suitable for engineering calculations. Hence, they are mainly applied to architecture and have
35 found very few applications in structural design. In addition, the considerable computational expense of the
36 underlying algorithms forfeits their use in the scheme design stage.

37 Deep learning methods offer a new option to overcome these challenges. They have been used efficiently for
38 various purposes via pre-training [9-13]. The generative adversarial network (GAN) is one of the most widely used
39 frameworks [14] for automated architectural design [15-17]. In this study, we extend the application of GAN to shear
40 wall structural design. The GAN model improves the design proficiency by learning from existing design documents,
41 thus offering a significant improvement in design efficiency and performance.

42 This paper presents the development and optimization of a GAN-based structural design framework, StructGAN,

and the associated engineer-perception-based and computer-vision-based performance metrics. By comparing designs by StructGAN and competent engineers, case studies of the GAN-based framework suggest that it is a promising and versatile design approach for the future.

Results

StructGAN

StructGAN was developed to address the growing concerns in the construction industry. Some of the negative impacts experienced include (1) the lack of an efficient communication link between architects and engineers, (2) the low cost-effectiveness in the design iterations, and (3) the quality uncertainties associated with experiential knowledge [18,19]. Therefore, process optimization and automation are necessary to minimize the total project time and cost. As such, StructGAN attempts to achieve the highest efficiency via artificial intelligence. It resolves the highly involving correlation between the architectural and structural fields through sophisticated maps established by deep learning, which converts the iterations to one-step solutions, reduces variations in design quality, and strengthens the control of design processes.

The strategic innovations adopted by StructGAN involve a semantic engagement of prior knowledge and high-level performance metrics. By activating experiential knowledge in structural engineering, StructGAN recognizes the crucial structural concepts, such as the locations of openings and the connectivity of structural components [8]. It abstracts the architectural schemes, extracts and color-codes the layout patterns, and make them structurally meaningful. The semanticization process reduces enormously the data dimension while keeping all the core information that can adequately inform the structural design, and ultimately boosts the design performance. To expedite the learning cycles, StructGAN abandons the traditional pixel-by-pixel evaluation, which fails to comprehend the overall structural layout. Instead, it adopts intersection over union (IoU) [20] as the core metric. The

65 IoU metric can properly gauge the overall similarity of the design under evaluation against the reference design and
66 provide valuable guidance and feedback to the training direction. These innovations provide a solid foundation for
67 the design performance that StructGAN delivers consistently to all types of building structures.

68 The components of StructGAN are summarized in Figure 1a: interpreter, designer, and modeler. The interpreter
69 digests and semanticizes the architectural sketches. Then, the designer analyzes the semantic drawings, performs the
70 inference, and devises the structural design. Finally, the modeler proposes the design and presents the structural
71 model. Figure 1b compares the performances of StructGAN and the conventional design process. StructGAN offers
72 a promising increase in speed by a factor of 10, which is equivalent to saving billions of US dollars per annum in the
73 industry. As it learns and evolves continuously, StructGAN will undoubtedly obtain much higher savings.

74

b

StructGAN performance	High efficiency		Superior quality	
	20 times faster	10 times faster	Comparable potential seismic loss (only 6% larger)	Excellent stability
Competent engineers	3.5 h / preliminary design	300 h / complete design	\$9,846,000 USD	Economic and mechanical performance of designs by inexperienced engineers are inferior to those by senior engineers
StructGAN	10 min / preliminary design	30 h / complete design	\$10,454,500 USD	Consistent design quality for structural designs with various heights and seismic design intensities

Fig. 1. StructGAN. **a**, The StructGAN automated structural design framework. Interpreter: digesting and semanticizing the architectural sketches. Designer: analyzing the semantic drawings and devising the structural design. Modeler: proposing the design and the corresponding structural model. **b**, The excellent performance of StructGAN, with high efficiency and superior quality. The estimation of design efficiency, safety, and economic performance are elaborated in the Methods section. The time consumption of competent engineers is derived from the study of Chakrabarti [21]. The potential seismic losses are analyzed by the widely adopted FEMA P58 method [22], and the values are the mean losses of two typical high-rise shear wall residential buildings.

83 StructGAN performance

84 This section further demonstrates the superior performance of StructGAN by comparing it against the structural
85 designs of competent engineers. The comparison is performed on the drawings first, followed by an evaluation of the
86 structural behavior. Two approaches based on computer vision and engineer perception were developed to support a
87 comprehensive assessment. Subsequently, two overall structural designs by StructGAN and engineers are compared
88 to show that the StructGAN designs are not only safe but also economical. The observations of similar material take-
89 offs and seismic resilience suggest that the structural design by StructGAN is as great as those optimized by
90 competent engineers.

91 In total, 16 structural design drawings by StructGAN and engineers were compared. Figure 2a illustrates four
92 typical structural plan designs for shear wall residential buildings, depicting the high consistency between the designs
93 by StructGAN and experienced engineers.

94 The computer-vision-based evaluation was performed first. The quality evaluation results of structural designs
95 by StructGAN are shown in Figure 2b. The metric $Score_{IoU}$ considers the comprehensive performance of structural
96 design and image generation. The consistency measurement basis for $Score_{IoU}$ is the IoU, which denotes the ratio of
97 the intersection area to the union area of structural designs by StructGAN and engineers. Previous studies indicated
98 that an $IoU > 0.5$ corresponds to a high consistency [23,24]. Moreover, in the comparison study of structural plan
99 layouts, 16 buildings were adopted as cases and divided into two groups according to their different design conditions.
100 Thus, the $Score_{IoU}$ in Figure 2b is the average of each group, and it is higher than 0.5, indicating that the structural
101 designs by StructGAN are comparable to those by experienced engineers and are outstanding.

102 Furthermore, engineers were also invited to judge the “AI” or “Engineer” of designs and assess the rationality
103 of StructGAN designs based on their straightforward perception. In the “AI” or “Engineer” judgment, engineers need
104 to figure out the ones designed by StructGAN, and the judgment score is S_{EP-1} . Simultaneously, in the design

105 rationality assessment, the rationality score is S_{EP-2} . This study invited 11 senior experts (work experience > 15 years),
106 12 practicing engineers, and graduate students to participate in the judgment and evaluation work. Two important
107 conclusions can be drawn from the results shown in Figure 2c. (1) Approximately 30% of the StructGAN designs
108 were appraised as designs by engineers, with the corresponding S_{EP-1} equal to 30%, which is notably better than the
109 highest Amazon Mechanical Turk (AMT) test result of 22.5% in the pix2pix study [25]. The above result indicates
110 that it was challenging for humans to distinguish the designs by engineers and StructGAN accurately. (2) The
111 difference in rationality quantification for structural shear wall design between the StructGAN and engineers was
112 approximately 12%, confirming that the StructGAN structural designs were excellent and highly accepted by
113 engineers.

114 Additionally, the architectural layouts of the 16 buildings are completely different, with seismic design
115 intensities of 7-degree and 8-degree, and heights of 28–140 m. The 16 cases were subdivided into groups of Group7-
116 H2 and Group8, where Group7-H2 denotes buildings designed under 7-degree seismic intensity and heights over 50
117 m, and Group8 denotes buildings designed under 8-degree seismic intensity. Notably, the corresponding peak ground
118 acceleration (PGA) values of the design basis earthquake (i.e., 10% probability of exceedance in 50 years) are 100
119 cm/s^2 and 200 cm/s^2 in the 7-degree and 8-degree seismic intensity zones, respectively.

120

Fig. 2. Evaluation results of the optimal StructGAN. **a**, Typical structural designs by StructGAN (red, gray, blue, and green denote structural shear wall, nonstructural infill wall, indoor windows, and outdoor gates, respectively). **b**, Computer vision-based evaluation results ($Score_{IoU} = \eta_{SWratio} \times (\eta_{S_{IoU}} \times S_{IoU} + \eta_{W_{IoU}} \times W_{IoU})$; $\eta_{SWratio} = 1 - |SWratio_{GAN} - SWratio_{target}| / SWratio_{GAN}$; $\eta_{S_{IoU}} = \eta_{W_{IoU}} = 0.5$). **c**, Engineer perception-based evaluation results, including “AI” or “Engineer” judgment and rationality quantification.

Subsequently, two overall structural designs by StructGAN and engineers were compared. The safety and economic properties are directly associated with seismic deformation and material consumption, respectively.

130 Adopting StructGAN, this study developed two structural designs following the guide in Figure 1a, and then
131 compared their safety and economic properties with those of the designs by competent engineers. The two buildings
132 are shown in Figures 3a and 3b.

133 First, structural safety is primarily evaluated by the seismic story drift ratio because excessive story deformation
134 under an earthquake can induce damage to structural components and facilities and even cause a large number of
135 casualties. Hence, ensuring that the seismic deformation of buildings satisfies the specifications is essential in the
136 overall structural design. The comparisons of seismic story drift ratios for two buildings are shown in Figures 3d and
137 3e. As depicted in the figures, the maximum seismic deformation of the StructGAN design is only 11% larger than
138 that of the design by engineers, which is perfectly acceptable in the preliminary design and meets the safety
139 requirements. Subsequently, this work compared the StructGAN designs and designs by engineers with respect to
140 material consumption, and the results are shown in Figure 3c. The maximum difference is within 5% in the two cases,
141 indicating that the automated designs consume almost the same amount of materials as manual designs and fully
142 meet the economic requirements. Additionally, the seismic repair costs of the StructGAN designs and designs by
143 engineers are comparable, as illustrated in Figure 3c. Consequently, the economic and safety differences in the
144 structural designs by StructGAN and experienced engineers are relatively slight, and the StructGAN design meets
145 the requirements of high efficiency and high quality in the preliminary structural design.

146

Fig. 3. Comparisons between the StructGAN designs and designs by engineers. The two cases are named Case-7degree and Case-8degree, with heights of approximately 100 m and seismic design intensities of 7-degree and 8-degree, respectively. **a**, 3D view of Case-7degree. **b**, 3D view of Case-8degree. **c**, Comparisons of overall performance in Case-7degree and Case-8degree. **d**, Comparisons of story drift ratios in Case-7degree. **e**, Comparisons of story drift ratios in Case-8degree.

Discussion

Detailed discussions and analyses on the StructGAN were conducted to obtain the aforementioned high-performance system, whose most critical parts are the GAN algorithm and dataset. Hence, the Discussion section presents the analysis for the selection of GAN algorithm and the corresponding parametric adjustment along with the

pre-processing of the datasets, based on the developed performance evaluation methods and metrics.

GAN algorithm and parametric adjustment

The pix2pix [25] and pix2pixHD [26] algorithms are typical high-performance GAN algorithms. Compared with pix2pix, pix2pixHD is an improved algorithm that can generate high-resolution photo-realistic images with significantly higher computational demands [26]. In the above two algorithms, the characteristic “structures loss” can effectively reflect the physical position relationship of pixels in an image [25]. Thus, deduced from the “structures loss,” pix2pix and pix2pixHD can capture the potential spatial position distribution of structural layouts. The structural distribution correlation can contribute to establishing a direct map relationship for StructGAN to convert the crucial architectural elements into the corresponding structural layouts. Furthermore, their significant performance in generative architectural design has proved the applicability of pix2pix and pix2pixHD [15,16]. Consequently, this work adopted them as core algorithms for StructGAN.

As recommended by Isola et al. [25] and Wang et al. [26], the performances of pix2pix and pix2pixHD are influenced by critical parameters; therefore, parametric studies should be conducted. In the pix2pix algorithm, the local features and global clarity of image qualities are primarily determined by the relative values of γ_{GAN} and γ_{LI} (i.e., $\gamma_{\text{GAN}} / \gamma_{\text{LI}}$) [25]. In the pix2pixHD algorithm, the vital hyperparameter γ_{FM} affects the overall quality of the generated image by adjusting the proportion of the feature matching loss to the total loss [26]. Furthermore, this work proposed a computer vision-based evaluation method and several metrics such as *PA*, *WIoU*, *SIoU*, and *SWratio* to pad the blank of the quantitative evaluation method and associated metrics for the structural design quality. Pixel accuracy (*PA*) evaluates the overall clarity of the generated image, weighted IoU (*WIoU*) focuses on assessing the generative qualities of critical elements in images, structural IoU (*SIoU*) explicitly measures the structural layout consistency between the designs by StructGAN and engineers, and the difference in *SWratio* estimates the

180 discrepancy of the total structural layout area between two designs. As these metrics show, a high PA , $WIoU$, and
181 $SIoU$ and low difference in $SWratio$ indicate that the designs by StructGAN and engineers are highly consistent.
182 Subsequently, this study discussed the influence of $(\gamma_{GAN} / \gamma_{LI})$ and γ_{FM} based on the proposed evaluations, where
183 γ_{GAN} was fixed as 1, and the Group7-H2 dataset of shear wall residential buildings was adopted.

184 Figures 4a and 4b show the typical design performance of pix2pix and pix2pixHD with various hyperparameters.
185 When $\gamma_{LI} = 0$, pix2pix loses its control on the global quality of image clarity, causing enormous noise in the generated
186 image. As γ_{LI} increases, the automated design quality is improved until it becomes stable, with the clarity of image
187 and the structural design rationality improving significantly. In comparison, γ_{FM} only slightly influenced the
188 automated design quality because it mainly affects feature mapping and this study involved the input of architectural
189 semantic images containing few local features. Moreover, quantitative evaluations were conducted to quantify the
190 design qualities of StructGAN with different hyperparameters. As Figures 4c–4f illustrate, PA , $WIoU$, and $SIoU$ grow,
191 and the difference in $SWratio$ degrades with increasing γ_{LI} and γ_{FM} . The evaluation results were consistent with the
192 perceptual results in Figures 4a and 4b, revealing that these methods and metrics are reasonable and applicable.
193 Furthermore, both the image generation and structural design qualities of pix2pixHD are significantly better than
194 those of pix2pix, with small design dispersion and high stability. The $WIoU$ and $SIoU$ of the pix2pixHD design with
195 the optimal parameters both exceed 0.5, indicating that the structural layout is very reasonable. The total amount of
196 structural shear walls designed by StructGAN is comparable to those designed by competent engineers, with a
197 difference in $SWratio$ smaller than 15%. Consequently, the evaluation results show that the designs by StructGAN
198 equipped with pix2pixHD coincide well with designs by engineers, with high stability. Meanwhile, the performance
199 of pix2pix still needs to be enhanced in future studies. Based on the discussions and recommendations by Wang et
200 al. [26], StructGAN adopts pix2pixHD, with $\gamma_{FM} = 10$.

Fig. 4. Analyses of the hyperparameters and quantification of testing results for different GAN algorithms

with various parameters. a, Comparison of the pix2pix-generated images with different parameters. b, Comparison

of the pix2pixHD-generated images with different parameters. c–f, Comparisons of *SIoU*, *WIoU*, *PA*, and the difference in *SWratio* between pix2pix and pix2pixHD with various parameters. The evaluation results show that the designs by StructGAN equipped with pix2pixHD coincide well with those by engineers, with high stability. However, the performance of pix2pix needs further enhancement in future studies.

Dataset analysis

The maximum likelihood estimation is the basis of GAN algorithms [14], making the probability distribution of designs and design quality closely related to the datasets; hence, this study discussed the influence induced by datasets under different design conditions. Building heights and seismic design intensities were adopted as the classification criteria of the datasets because they are the critical factors that determine the mechanical performance of building structures. Higher heights and seismic design intensities correspond to increased requirements for structural components [8]. Notably, utilizing mixed design datasets with different heights and seismic design intensities for training, the final probability distributions of the automated designs were consistent with the average probability distribution of the mixed data, which cannot satisfy the demand for different design conditions. Therefore, datasets were divided into Group7-H1 (seismic design intensity = 7-degree, and height ≤ 50 m), Group7-H2 (seismic design intensity = 7-degree, and height > 50 m), and Group8 (seismic design intensity = 8-degree). In addition, for contrast, Group Mix (mixed dataset) was composed of various data.

Based on different training sets, this work obtained the GAN models called M-G7H1, M-G7H2, M-G8, and M-Mix. Subsequently, the testing sets of Group7-H1, Group7-H2, and Group8 were adopted to evaluate the design quality of the trained models. The testing results in Figures 5b–5d indicate that the best designs for the testing sets of Group7-H1, Group7-H2, and Group8 were produced by M-G7H1, M-G7H2, and M-G8, respectively, and the corresponding quantitative evaluation results are shown with orange backgrounds. Specifically, in the designs of

Figures 5b–5d, the best designs by StructGAN are highly consistent with the designs by experienced engineers (Figure 5a), with the positions and lengths of structural shear walls highly comparable. $SIoU$ and $WIoU$ are higher than 0.5, and the $SWratios$ of StructGAN designs are close to those of designs by engineers, indicating that the qualities of structural layouts are excellent. Overall, when the test design conditions match the training structural design conditions, both the layouts and total numbers of the structural shear walls designed by StructGAN are comparable to those in the designs by competent engineers.

Additionally, the quantitative evaluation results for all structural designs are shown in Figure 5e, indicating that the best designs were devised by the StructGAN trained under the consistent design conditions, with the largest corresponding $Score_{IoU}$. In addition, the design qualities of the adequately trained StructGAN under different design conditions are relatively stable, with their $Score_{IoU} > 0.5$. Hence, the training datasets for StructGAN should be classified based on design conditions, and the design conditions of the adopted StructGAN should be matched with those of architectural sketches in a structural design application. In contrast, the designs by StructGAN with unmatched design conditions are irrational. The layouts and length of the structural shear walls in the designs by StructGAN are inconsistent with those in the designs by competent engineers, as shown in Figure 5. Furthermore, the designs developed by M-Mix are close to the average of mixed designs, not precisely satisfying the demands of different design conditions. Consequently, refined design conditions-based data classification narrows the restriction of the maximum likelihood estimation and further improves the precision performance of StructGAN. Meanwhile, the design quality evaluation results confirmed the precise and stable design performance of StructGAN.

a. Target designs

b. Test (Group7-H1)

c. Test (Group7-H1)

d. Test (Group8)

e

Testing sets	SloU				WIoU			
	M-G7H1	M-G7H2	M-G8	M-Mix	M-G7H1	M-G7H2	M-G8	M-Mix
T-G7H1	0.41	0.46	0.44	0.52	0.59	0.55	0.47	0.57
T-G7H2	0.38	0.58	0.62	0.57	0.53	0.63	0.61	0.63
T-G8	0.37	0.60	0.74	0.67	0.51	0.62	0.72	0.64

Testing sets	SWratio _{target}	M-G7H1		M-G7H2		M-G8		M-Mix	
		SWratio _{GAN}	1 - $\eta_{SWratio}$	SWratio _{GAN}	1 - $\eta_{SWratio}$	SWratio _{GAN}	1 - $\eta_{SWratio}$	SWratio _{GAN}	1 - $\eta_{SWratio}$
T-G7H1	0.41	0.50	20%	0.69	41%	0.80	49%	0.65	37%
T-G7H2	0.58	0.44	35%	0.66	14%	0.74	23%	0.64	12%
T-G8	0.66	0.43	59%	0.67	14%	0.76	13%	0.71	9%

Testing sets	Score _{IoU}			
	M-G7H1	M-G7H2	M-G8	M-Mix
T-G7H1	0.40	0.31	0.24	0.35
T-G7H2	0.30	0.52	0.48	0.53
T-G8	0.18	0.53	0.65	0.61

Fig. 5. Typical testing designs of different trained StructGANs. a, Typical target designs of different groups. b, c,

d, Typical automated designs by different trained StructGAN models for testing groups of Group7-H1, Group7-H2,

and Group8. **c**, Quantitative evaluation results for all automated designs by different trained StructGAN models for testing groups of Group7-H1, Group7-H2, and Group8. The most critical metric is $Score_{IoU}$, with value > 0.5 denoting excellent quality. $Score_{IoU} = \eta_{SWratio} \times (\eta_{SloU} \times SloU + \eta_{WIoU} \times WIoU)$; $\eta_{SWratio} = 1 - |SWratio_{GAN} - SWratio_{target}| / SWratio_{GAN}$; $\eta_{SloU} = \eta_{WIoU} = 0.5$.

This study validated the efficiency and accuracy of the proposed StructGAN framework via discussions and analyses. The excellent design performance was obtained through the optimal algorithm, the most applicable hyperparameters, the proposed dataset split method, and rational evaluation methods. Notably, the Methods section illustrates with further detail the framework and implementation of StructGAN.

Conclusions

A GAN-based method for the structural design of high-rise shear wall residential buildings (i.e., StructGAN) was proposed in this study, mastering the direct map relationship for converting critical architectural elements into the corresponding structural designs. Moreover, a reasonable evaluation system and the corresponding metrics were developed and adopted in the discussions and analyses of GAN algorithms and datasets, enhancing the learning and design performance of StructGAN. The outstanding StructGAN provides preliminary structural design schemes for architects and structural engineers, improving the design efficiency and quality of building structures. The conclusions drawn are as follows:

1. Semantic designs can reduce the probability distribution dimension of the StructGAN training dataset and enhance its study performance. Dataset classification by building heights and seismic design intensities can narrow the restriction of the maximum likelihood estimation, improving the precision of generative designs by StructGAN.

2. pix2pixHD ($\gamma_{FM} = 10$) is recommended for StructGAN owing to its high-quality design capability with high

efficiency and stability. An appropriate simplification of the generative network architecture of pix2pixHD is beneficial for further enhancing the design precision of StructGAN.

3. Computer vision-based and engineering-perception-based evaluation methods were developed and adopted in this study. The computer vision-based evaluation quantifies and confirms the design quality of StructGAN, and the engineer perception-based evaluation indicates that engineers highly accept the StructGAN designs.

Notably, this study is the first to propose a GAN-aided structural design method by establishing the complicated fuzzy map relationship for converting semantic architectural sketches into structural layouts, which can also be an automated design basis for other structural systems, bridges, and tunnels. Moreover, as the design data and GAN capability increase, the design performance of StructGAN is continuously enhanced.

Methods

Background and implementation of StructGAN

In a GAN framework, the generative network learns to generate candidates of interest, while the discriminative network distinguishes the generated candidates from the ground truth [14]. Extended Data Fig. 1a shows the training process of GAN-based image generation. The generator synthesizes images using the initial input noises and enhances the generation quality based on the feedback from the discriminator until the discriminator fails to judge. Simultaneously, the discriminator consistently elevates the skill at detecting synthetic outputs by the generator. Adversarial training is applied to both networks so that the generator and discriminator can master the generation and discrimination, respectively [14,25]. Additionally, compared with the convolutional neural network (CNN)-generated images, GAN-synthesized images are more refined and precise [25]. GAN has been successfully adopted in innovative architectural home design [15-17]. Hence, this study aims to extend the GAN-based design methods to structural design by learning from previous design experience.

A GAN-based automated structural design method was developed in this study, namely StructGAN. The StructGAN implementation is illustrated in Extended Data Figs. 1b–1d, including three dominating steps: (1) datasets and StructGAN training, (2) StructGAN performance evaluation, and (3) StructGAN application.

Datasets and StructGAN training

GAN learns from previous designs based on maximum likelihood estimation, making the probability distributions and qualities of the StructGAN design directly associated with the training datasets. Thus, to ensure the quality of the source design, this study applied approximately 250 pairs of architectural–structural designs from more than ten famous architectural design and research institutes in China. Moreover, these designs satisfied all relevant design specifications, were optimized and evaluated by experienced engineers, and were adopted in real-world construction applications with excellent quality. Subsequently, based on raw design datasets, semanticization and classification were conducted for the designs.

This study adopted the semantic process by extracting essential architectural and structural elements in design images and coding them by color patterns, so that critical design elements and the corresponding structural layout information are maintained. Semantic designs can effectively reduce the dimension of probability distributions and enhance training performance. In this study, the red (i.e., RGB = (255, 0, 0)), gray (i.e., RGB = (132, 132, 132)), green (i.e., RGB = (0, 255, 0)), and blue (RGB = (0, 0, 255)) colors denote the structural shear wall, nonstructural infill wall, indoor window, and outdoor gate, respectively.

In addition, the structural design for shear wall residential buildings is directly related to the design conditions of structural heights and seismic design intensities, and design conditions-based dataset classification can efficiently narrow the learning restriction of StructGAN to promote design precision. According to the *Chinese Code for Seismic Design of Buildings* [27], the datasets were classified into 7-degree and 8-degree seismic intensities. Notably, the

corresponding peak ground acceleration (PGA) values of the design basis earthquake (i.e., 10% probability of exceedance in 50 years) are 100 cm/s^2 and 200 cm/s^2 in the 7-degree and 8-degree seismic intensity zones, respectively. Subsequently, based on the structural height regulations in the *Chinese Technical Specification for Concrete Structures of Tall Buildings* [28], the datasets are classified into H1 (i.e., height $\leq 50 \text{ m}$) and H2 (i.e., height $> 50 \text{ m}$). In addition, the maximal building height is 141 m. The high seismic design intensity dominates the demands for structural seismic resistance in the 8-degree seismic intensity zones with slight influence of structural heights; thus, the designs in the 8-degree seismic intensity zones were not divided by heights. Consequently, the datasets were classified and named Group7-H1, Group7-H2, and Group8, respectively. GroupMix was built by randomly selecting 26 designs from each group and mixed for contrast. There are 63, 80, 81, and 78 training sets in the different groups and 8, 8, 8, and 0 testing sets, respectively. Typical datasets are shown in Extended Data Fig. 2.

Based on the pre-processed datasets, the StructGAN could be trained effectively. Except for the regular training recommended by pix2pixHD [26], in terms of the determined StructGAN system, this study also proposed performance enhancement approaches by (1) data augmentation and (2) parametric adjustment for the generative network architecture of pix2pixHD. The datasets were augmented by flipping the images vertically and horizontally and rotating the images 180° . This was done because the flip and rotation operations do not change the spatial layout of the structural shear walls in the image, and the number of Group7-H2 training data reasonably increased from 80 to 320. Furthermore, the complexity of local features is significantly reduced owing to the semantic architectural-structural designs; hence, the generator architecture can be simplified to generate more confined and precise image elements. The numbers of global down-sample layers ($n_{\text{downsample_global}}$) and residual blocks in the global generator network ($n_{\text{blocks_global}}$) were reduced from 4 to 2 (or 1) and from 9 to 6, respectively. Consequently, the StructGAN design performance was improved, with more integrated auto-designed structural shear walls and higher $Score_{IoU}$, as shown in Extended Data Fig. 3. For the Group8 dataset, the performance was not enhanced because

the normal method was sufficiently good. Simultaneously, the performance of StructGAN using Group7-H1 and Group7-H2 for training was obviously enhanced. Consequently, the improved StructGAN is recommended for automated structural design.

Evaluation and metrics

Accurate quality evaluation of GAN-synthetic images is vital and challenging for GAN-related studies [29]. The critical content of evaluation is the difference quantification of generations and targets. For images with high-dimensional probability distributions, the detailed evaluations are listed in Extended Data Fig. 4 [25,26,29-39], including (1) Amazon Mechanical Turk (AMT) perceptual studies, and (2) a computer vision-based assessment of synthetic images. However, compared with the image assessments, the evaluations for structural design are more complicated to reasonably consider the structural layouts and their correlations. Hence, based on the widely adopted AMT perceptual evaluation and image pixel-based evaluation, this study developed an engineer perception-based and computer vision-based evaluation method, assessing the rationality of the structural layout.

Engineer perception-based evaluation: the evaluation based on engineer perception is the most straightforward method to identify the acceptance by engineers of the StructGAN design capabilities. It includes (1) “AI” or “Engineer” judgment, which involves inviting engineers to distinguish designs produced by StructGAN or competent engineers, and (2) rationality score for designs, which comprises asking for scores given by engineers based on their experience and perception. Similar to the AMT method, the engineer perception-based evaluation was conducted on the Questionnaire Star (<https://www.wjx.cn/>) platform for blind tests, and typical parts of the questionnaire are illustrated in Extended Data Fig. 5. This study invited 11 senior experts (work experience > 15 years), 12 practicing engineers, and graduate students to participate in the judgment and assessment tasks, and the corresponding metrics were proposed based on the evaluation results. S_{EP-1} is the metric for the “AI” or “Engineer”

359 judgment, expressed in Equation (1), and which equally counts the judgment of experts and ordinary engineers. S_{EP-1}
 360 S_{EP-2} is the metric for rationality evaluation, expressed in Equation (2), and which adopts the coefficient of the variation
 361 to weight the scores by experts and ordinary engineers (Equation (3)).

362

$$S_{EP-1} = \frac{1}{N_{ex} + N_{nonex}} \sum_i^{N_{ex} + N_{nonex}} \frac{N_{FP}}{N_{FP} + N_{TN}} \quad (1)$$

$$S_{EP-2} = \eta_{ex} \frac{1}{N_{ex}} \sum_i^{N_{ex}} \left(\frac{1}{N_{img}} \sum_j^{N_{img}} S_j \right) + \eta_{nonex} \frac{1}{N_{nonex}} \sum_i^{N_{nonex}} \left(\frac{1}{N_{img}} \sum_j^{N_{img}} S_j \right) \quad (2)$$

$$\eta_{ex} = \frac{\sigma_{nonex} / \mu_{nonex}}{\sigma_{ex} / \mu_{ex} + \sigma_{nonex} / \mu_{nonex}}; \eta_{nonex} = 1 - \eta_{ex} \quad (3)$$

363 where N_{ex} and N_{nonex} denote the number of experts and non-experts, respectively, and N_{FP} and N_{TN} indicate the number
 364 of misjudgments and correct judgments of StructGAN designs, respectively. N_{img} is the number of assessed images,
 365 S_j is the score of image j , and η_{ex} and η_{nonex} are the weight coefficients of the scores of experts and non-experts,
 366 respectively. σ_{ex} and σ_{nonex} are the standard deviations of the scores of experts and non-experts, respectively, and μ_{ex}
 367 and μ_{nonex} are their mean values, respectively. The determination of the weight coefficients in Equation (3) refers to
 368 the coefficient of the variation-based method proposed by Diakoulaki et al. [40], where a smaller coefficient of
 369 variation corresponds to a higher weight.

370

Fig. 6. Computer vision-based evaluation. **a**, Confusion matrix used to obtain PA , $WIoU$, and $SWratio$. **b**, Detailed steps to get $SloU$. **c**, Typical cases of $SloU$.

Computer vision-based evaluation: the integrated consideration of the generated image quality and rationality of the structural design by StructGAN is a significant advantage of the proposed computer vision-based evaluation method. In general, the simultaneous quality evaluation of synthetic images and structural designs is challenging. This study adopted a confusion matrix [41] to assess the generation quality of critical elements in images and IoU of structural layouts to assess the rationality of the structural design. Subsequently, two methods are weighted to evaluate the comprehensive performance of StructGAN.

In the confusion matrix-based assessment, adopting the classification of each pixel and the correctness judgment of the pixel type to evaluate the generative quality is the core superiority. First, structural shear walls, nonstructural infill walls, indoor windows, and outdoor gates are directly distinguished and separated according to the hue

saturation value (HSV) of each pixel, utilizing the Open Source Computer Vision (OpenCV) library for image processing to convert the colors into the HSV mode [42] (Extended Data Figs. 6a and 6b). The extracted elements of the StructGAN design are compared with those of engineers pixel-by-pixel, and then the comparison results are used to create a confusion matrix (Figure 6a). Subsequently, based on the confusion matrix, PA , $WIoU$, and $SWratio$ are proposed and used, where PA (Equation (4)) measures the image clarity, $WIoU$ (Equation (5)) estimates the generative quality of critical elements, and $SWratio$ (Equation (6)) reflects the total amount of structural shear walls. Owing to the above-proposed metrics derived from image pixel classification, the use of the confusion matrix-based evaluation could measure the comprehensive quality of the generated image.

$$PA = \frac{\sum_{i=0}^k p_{ii}}{\sum_{i=0}^k \sum_{j=0}^k p_{ij}} \quad (4)$$

$$WIoU = \sum_{i=0}^k \frac{w_i \sum_{j=0}^k p_{ij} p_{ii}}{\sum_{j=0}^k p_{ij} + \sum_{j=0}^k p_{ji} - p_{ii}} \quad (5)$$

$$SWratio = \frac{A_{\text{swall}}}{A_{\text{swall}} + A_{\text{inwall}}} \quad (6)$$

where $(k+1)$ is the total class (class 0 is background, class 1 is shear wall, class 2 is infill wall, class 3 is window, class 4 is outdoor gate), p_{ij} is the number of pixels of class i inferred to belong to class j . In other words, p_{ii} represents the number of true positives, whereas p_{ij} and p_{ji} are usually interpreted as false positives and false negatives, respectively. $w_0 = 0$, $w_1 = 0.4$, $w_2 = 0.4$, $w_3 = 0.1$, and $w_4 = 0.1$; the synthetic results of the shear wall and infill wall are the most essential, and hence, their weights are the largest. A_{swall} and A_{inwall} are the total areas of the shear wall and infill wall, respectively.

In the structural IoU-based evaluation, the core superiority is the consistency measurement of the structural layouts designed by StructGAN and experienced engineers. Detailed steps for the structural IoU-based evaluation are illustrated in Figure 6b, and the corresponding metric is named *SIoU* (structural intersection over union). First, the images are subdivided into multiple sub-images to reduce the number of structural shear walls in each image and elevate the edge capture precision of the contour detection algorithm. Subsequently, the shear wall elements of each sub-image are extracted based on the HSV color mode, and their contour coordinates are identified by the contour detection API “*OpenCV.findContours (image)*.” Then, the total intersection area of the shear walls in the StructGAN design and design by engineers are obtained using the Shapely API “*shapely.geometry.Polygon (coordinates)*” and *SIoU* is calculated using Equation (7).

$$SIoU = \frac{A_{\text{inter}}}{A_{\text{union}}} \quad (7)$$

where A_{inter} is the intersection area of the walls in the GAN-synthetic and target designs, A_{union} is the union area of the walls in the GAN-synthetic and target designs, $A_{\text{union}} = A_{\text{target}} + A_{\text{GAN}} - A_{\text{inter}}$, and A_{target} , and A_{GAN} denote the shear wall area of the target design and the GAN design, respectively.

Inferring from the above studies of single metrics, *PA* is the traditional pixel-by-pixel evaluation to assess the image quality, which is abandoned because of the failure to comprehend the overall structural layout. Moreover, *SIoU*, *WIoU*, and *SWratio* can only evaluate the confined properties of structural layouts of StructGAN. Hence, by combining the qualities of the generated critical elements in images and structural designs, this study proposed the weighted multi-metric *Score_{IoU}* (Equation (8)).

$$Score_{IoU} = \eta_{SWratio} \times (\eta_{SIoU} \times SIoU + \eta_{WIoU} \times WIoU) \quad (8)$$

where $\eta_{SWratio} = 1 - |SWratio_{GAN} - SWratio_{target}| / SWratio_{GAN}$. $SWratio_{GAN}$, and $SWratio_{target}$ are the shear wall ratios of the GAN designs and target designs, respectively. η_{SIOU} and η_{WIoU} are the weighted coefficients of $SIOU$ and $WIoU$, respectively, both equal to 0.5.

For the evaluation of the StructGAN-designed shear wall layouts, $WIoU$, which reflects the generation quality of the overall walls in images, and $SIOU$, which reflects the quality of the auto-designed structural shear wall layouts, are equally important. Thus, the weights η_{SIOU} and η_{WIoU} are set to 0.5. Moreover, the $\eta_{SWratio}$ denotes the correction coefficient for the overall quantity of shear walls. The values of $WIoU$ and $SIOU$ increase with the increment in shear walls, which is unfavorable for the evaluation. Hence, the difference in the total shear wall area between the synthetic image and target image is adopted as the correction coefficient, and a smaller diversity corresponds to a larger $\eta_{SWratio}$.

StructGAN application

StructGAN is primarily developed for the preliminary schematic design, and partly for structural design development, following the guide in Figure 1. Specifically, in the StructGAN application, the semanticization of architectural drawings requires approximately 9 min, and then the semantic drawings are input into StructGAN to generate the corresponding structural layout design, which takes approximately 30 s. Compared with the design of experienced engineers, adopting StructGAN for preliminary structural design can reduce the time consumption from 3.5 h to 10 min. Additionally, StructGAN can also improve the efficiency of the overall structural design. As an estimation of this study, time consumption can be reduced from 300 h to 30 h with ten times efficiency enhancement. Furthermore, standardizing the semanticization process of architectural drawings can shorten the time of preliminary structural design to 3 min, with higher overall design efficiency. StructGAN accelerates the entire structural design process by a factor of 10, which is equivalent to a saving of approximately 100 million USD per annum in the industry,

442 according to the statistical estimation of this work. See Extended Data Detailed Process a [19] for additional
443 estimation information.

444 The StructGAN application results have been elaborated in the Results section, including 16 structural plan
445 designs and two overall structural designs for shear wall residential buildings. This study ensured no data crossover
446 between the training sets and 16 testing cases for testing reliability. To avoid information leak more strictly, the two
447 cases (Extended Data Figs. 7a and 7b) for the overall structural design were supplied by an architectural design and
448 research institute in China, and the designs were not adopted in the training and test. These application results
449 validated the StructGAN with a powerful generalization ability for different design conditions.

450 Furthermore, the detailed process of converting the structural plan design into an overall structural analysis
451 model is as follows:

- 452 • Quantitative evaluation of the design images based on $Score_{IoU}$: The structural plan design is first obtained by
453 StructGAN and evaluated by comparison with designs by engineers, as shown in Extended Data Figs. 7c and
454 7d. The comprehensive evaluation scores ($Score_{IoU}$) of the shear wall design images for Case-7degree and Case-
455 8degree are illustrated in Extended Data Fig. 7e, and both exceed 0.5, indicating that the validation results are
456 excellent.
- 457 • Establishment of the corresponding structural analysis models based on the StructGAN designs: The detailed
458 process of converting the bitmap of the shear wall design into a structural analysis model is shown in Extended
459 Data Detailed Process b.
- 460 • Performance analysis of structures: This study used the PKPM software to conduct overall structural design and
461 time-history analyses [43], and then yielded the direct economic loss under the maximum considered earthquake
462 using the FEMA P58 method [22].

463

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543

Appendix

Extended Data Fig. 1. The framework of StructGAN. a, Generative adversarial network [25]. b, Training. c, Evaluation. d, Application.

a **b**

Category	Training		Testing	
	Quantity	<i>SWratio</i>	Quantity	<i>SWratio</i>
Group7-H1	63	0.43 ± 0.08	8	0.40 ± 0.10
Group7-H2	80	0.57 ± 0.08	8	0.57 ± 0.08
Group8	81	0.67 ± 0.14	8	0.66 ± 0.11
GroupMix	78	0.55 ± 0.14	24	0.55 ± 0.15

Extended Data Fig. 2. Datasets for GAN training. **a**, Typical training-testing sets. (the top row A shows the input architectural design images, and the bottom row B is the corresponding target structural design images). **b**, Different datasets classified by structural height and seismic design intensity. (*SWratio* denotes the ratio of shear walls to total walls, reflecting the area proportion of the shear walls to the total walls).

Target (L2-7, NO.9)	Normal ($SWratio = 0.67$, $SIoU = 0.54$,	Enhanced ($SWratio = 0.64$, $SIoU = 0.69$,
$SWratio = 0.54$	$WIoU = 0.69$, $Score_{IoU} = 0.50$)	$WIoU = 0.60$, $Score_{IoU} = 0.52$)

Datasets		$SWratio_{GAN}$ ($SWratio_{Target}$)	$SIoU$	$WIoU$	$Score_{IoU}$ ($(\eta_{SWratio} \times (\eta_{SIoU} \times SIoU + \eta_{WIoU} \times WIoU))$)	Improvement ratio
G7-H1	Normal	0.50 (0.41)	0.41	0.59	0.40	10%
	Enhanced	0.53 (0.41)	0.54	0.61	0.44	
G7-H2	Normal	0.66 (0.58)	0.58	0.63	0.52	0%
	Enhanced	0.74 (0.58)	0.68	0.64	0.52	
G8	Normal	0.76 (0.66)	0.74	0.72	0.65	-1.5%
	Enhanced	0.74 (0.66)	0.75	0.70	0.64	

Extended Data Fig. 3. The performance of the enhanced StructGAN

References	Pascal tests (quantitative evaluation)		Perceptual tests
	Method	Metric	(qualitative evaluation)
Springenberg, 2015 [30]	/	Log-likelihood by Parzen-window estimate	/
Salimans et al., 2016 [29]	Classification	Classification error	AMT
Isola et al., 2017 [25]	Segmentation (FCN-8s)	Per-pixel acc., Per-class acc., IoU	AMT
Zhang et al., 2016 [31]	Classification (VGG; ImageNet)	mAP	AMT
	Detection		
	Segmentation	IoU	
Zhu et al., 2017 [32]	Segmentation	Per-pixel acc., Per-class acc., IoU	AMT
Wang et al., 2018 [26]	Segmentation	Pixel acc.; IoU	AMT
Wang & Gupta, 2016 [33]	Classification (Places-AlexNet)	Maximum norm $\ \cdot\ _\infty$ of the softmax output (i.e., the maximum probability)	AMT
	Detection (Fast-RCNN detector)	Number of objects	

Extended Data Fig. 4. Review of quality evaluation methods. Segmentation is derived from the studies of semantic segmentation [35,36]; Detection is derived from the studies of object detection [37-39]. (“mAP” denotes mean average precision; “acc.” denotes accuracy; “IoU” denotes intersection over union; “AMT” denotes Amazon mechanical turk.)

1. Please distinguish the following images: AI-generated or Engineer-designed?

(Red - shear wall; Gray - infill wall; Green - window; Blue - outdoor gate)

[Choice] *

- ☐ AI-generated ☐ Engineer-designed

Reasonability score of the shear wall design (1 - Unreasonable, 5 - Reasonable)

[Choice] *

- ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Extended Data Fig. 5. Evaluation based on engineer perception evaluation

Extended Data Fig. 6. Information on evaluation. **a**, The value range of 5 colors in the HSV color mode. **b**, The critical extracted elements of the target image. **c**, The critical extracted elements of the generated image.

Step1: The pixel class is directly distinguished and separated according to the hue saturation value (HSV) of each pixel in the image. The red-green-blue (RGB) mode values of the different colors are discrete and unfavorable for use in the color classification. Consequently, the Open Source Computer Vision (OpenCV) library is used for image processing to convert the colors into HSV mode.

Step2: The pixel category matrix of the image is obtained via the pixel classification. Each element of the matrix correlates to the classification result of the corresponding pixel. Then the matrix is reshaped into a pixel category vector. Subsequently, the confusion matrix is obtained by inputting the pixel category vectors of the synthetic and target images into the Scikit-learn application programming interface (API) "*sklearn.metrics.confusion_matrix(y_true, y_pred)*".

Extended Data Fig. 7. Information on case studies. **a, b,** The plan layout of the standard story in Case-7degree and Case-8degree, respectively. **c, d,** Comparisons of shear wall designs by StructGAN and engineer in Case-7degree and Case-8degree, respectively. **e,** The quantification evaluation of the validation results.

Extended Data Detailed Process. **a**, Potential profit from StructGAN. **b**, Extension of structural plane design to overall structural design.

a, Potential profit from StructGAN

Approximately \$265 billion annual profit pool awaits disrupters in the construction industry, according to McKinsey [19]. The total cost of architectural design accounts for approximately 2.5% of the entire construction cost, and the preliminary design accounts for approximately 5% of the architectural design cost. StructGAN accelerates the design process and reduces the time consumption by approximately 1/3. Hence, the potential profit created by StructGAN equals 110 million USD ($= 265 \text{ billion} \times 2.5\% \times 5\% \times 33.3\%$).

b, Extension of the structural plane design to the overall structural design.

(1) The bitmap of the shear wall design was attached to the AutoCAD drawing of the original architectural design using the attach function in AutoCAD.

(2) The coordinates and length of the StructGAN-designed shear walls are obtained using the dimension function in AutoCAD.

(3) The structural analysis model is established based on the original structural model and the shear wall coordinates obtained in Step 2 using the PKPM software.

(4) The following principles are adopted for establishing the structural analysis model. In the event that certain pixels of the auto-designed shear wall are missing, the shear wall is considered continuous if pixels of the shear wall exist within that length. Shear walls with a length shorter than the wall thickness (i.e., 200 mm) are excluded. Only the shear wall length of the structural design of the StructGAN is adjusted without altering any other properties, such as the section thickness and material properties, to maintain a better comparison of the designs of the StructGAN and engineered design. After the shortening (or extension) of the shear wall length, the connected beams are extended (or shortened) to maintain the completeness of the structural analysis model.

Figures

Figure 1

StructGAN. a, The StructGAN automated structural design framework. Interpreter: digesting and semanticizing the architectural sketches. Designer: analyzing the semantic drawings and devising the structural design. Modeler: proposing the design and the corresponding structural model. b, The excellent performance of StructGAN, with high efficiency and superior quality. The estimation of design efficiency, safety, and economic performance are elaborated in the Methods section. The time consumption of competent engineers is derived from the study of Chakrabarti [21]. The potential seismic losses are

analyzed by the widely adopted FEMA P58 method [22], and the values are the mean losses of two typical high-rise shear wall residential buildings.

Figure 2

Evaluation results of the optimal StructGAN. a, Typical structural designs by StructGAN (red, gray, blue, and green denote structural shear wall, nonstructural infill wall, indoor windows, and outdoor gates, respectively). b, Computer vision-based evaluation results ($Score_{IoU} = \eta_{SWratio} \times (\eta_{S_{IoU}} \times S_{IoU} + \eta_{W_{IoU}} \times W_{IoU})$; $\eta_{SWratio} = 1 - |SWratio_{GAN} - SWratio_{target}| / SWratio_{GAN}$; $\eta_{S_{IoU}} = \eta_{W_{IoU}} = 0.5$). c, Engineer perception-based evaluation results, including "AI" or "Engineer" judgment and rationality quantification.

Figure 3

Comparisons between the StructGAN designs and designs by engineers. The two cases are named Case-7degree and Case-8degree, with heights of approximately 100 m and seismic design intensities of 7-degree and 8-degree, respectively. a, 3D view of Case-7degree. b, 3D view of Case-8degree. c, Comparisons of overall performance in Case-7degree and Case-8degree. d, Comparisons of story drift ratios in Case-7degree. e, Comparisons of story drift ratios in Case-8degree.

Figure 4

Analyses of the hyperparameters and quantification of testing results for different GAN algorithms with various parameters. a, Comparison of the pix2pix-generated images with different parameters. b, Comparison of the pix2pixHD-generated images with different parameters. c–f, Comparisons of SloU, WIoU, PA, and the difference in SWratio between pix2pix and pix2pixHD with various parameters. The evaluation results show that the designs by StructGAN equipped with pix2pixHD coincide well with those

by engineers, with high stability. However, the performance of pix2pix needs further enhancement in future studies.

Figure 5

Typical testing designs of different trained StructGANs. a, Typical target designs of different groups. b, c, d, Typical automated designs by different trained StructGAN models for testing groups of Group7-H1, Group7-H2, and Group8. e, Quantitative evaluation results for all automated designs by different trained

StructGAN models for testing groups of Group7-H1, Group7-H2, and Group8. The most critical metric is ScoreIoU, with value > 0.5 denoting excellent quality. $\text{ScoreIoU} = \eta \text{SWratio} \times (\eta \text{SloU} \times \text{SloU} + \eta \text{WIoU} \times \text{WIoU})$; $\eta \text{SWratio} = 1 - |\text{SWratioGAN} - \text{SWratio}_{\text{target}}| / \text{SWratio}_{\text{GAN}}$; $\eta \text{SloU} = \eta \text{WIoU} = 0.5$.

Figure 6

Computer vision-based evaluation. a, Confusion matrix used to obtain PA, WIoU, and SWratio. b, Detailed steps to get SloU. c, Typical cases of SloU.

Supplementary Files

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