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Generative Adversarial Networks in the Built Environment: A Comprehensive Review of the Application of GANs across Data Types and Scales

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Abstract

Generative Adversarial Networks (GANs) are a type of deep neural network that have achieved many state-of-the-art results for generative tasks. GANs can be useful in the built environment, from processing large-scale urban mobility data and remote sensing images at the regional level, to performance analysis and design generation at the building level. We analyzed 100 articles to provide a comprehensive state-of-the-art review on how GANs are currently applied to solve challenging tasks in the built environment. Our results show that: (i) GANs are replacing older methods in some problems and setting state-of-the-art performances; (ii) GANs are opening new frontiers in previously overlooked problems, such as automatically generating spatially accurate floorplan layouts; (iii) GANs can be applied to different scales in the built environment, from entire cities to neighborhoods and buildings; and (iv) GANs are being used in a variety of problems and data types, from remote sensing data augmentation, vector data generation, spatio-temporal data privacy protection, to building design generation. In total, there are 26 unique application domains enabled by GANs; (v) however, one common challenge in this field currently is the lack of high-quality datasets curated specifically for problems in the built environment. With more data in the future, GANs could potentially produce even better results than today.

Keywords: Machine Learning, Generative Design, Urban Planning, GeoAI, Urban AI

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1. Introduction

Generative Adversarial Networks (GANs) are a type of deep neural network that have achieved many state-of-the-art results for generative tasks such as data augmentation, data synthesis, and design automation.

GANs are made up of two components, a generator and a discriminator pair. The generator attempts to generate samples that will pass the scrutiny of the discriminator, and the discriminator tries to distinguish the synthetic samples from the real samples. During training, the generator and the discriminator pit against each other in a zero-sum game, each trying to outperform the other. Eventually, a state of equilibrium is reached and the generator could produce synthetic samples indistinguishable from the ground truth by the discriminator.

The most researched application of GANs is in computer vision, breaking ground in image generation, translation, and enhancement (Wang et al., 2017b; Aggarwal et al., 2021; Gui et al., 2021a). Equipping GANs with Convolutional Neural Networks (CNNs) (Radford et al., 2015), GANs can generate realistic-looking synthetic photos of human faces, street view images, and satellite images that could pass as real photos to humans (Brock et al., 2018; Zakharov et al., 2019; Karras et al., 2021; Zhao et al., 2021a; Toker et al., 2021; Biljecki and Ito, 2021). GANs can also be used in content-aware image inpainting to fill missing areas in an image (Li et al., 2017; Yeh et al., 2017; Pathak et al., 2016). Some GAN architectures even allow for semantic control of the generated images (Isola et al., 2017; Park et al., 2019). A mask-image pair can be used for training, where the model could learn to translate color-coded masks into realistic images or to translate photos into different stylistic expressions (Zhu et al., 2017).

In addition to images, the generative prowess of GANs can be applied to other data formats as well. By designing different neural network layers in the generator and discriminator, sequential data such as text and unstructured data such as graphs can all be ingested and learned by the network. This data-agnostic nature has expanded the potential applications of GANs to a wider range of generative problems and has already established the state-of-the-art in many applications such as speech enhancement, music composition, fault detection, and graph-based prediction (Pascual et al., 2017; Dong et al., 2018; Lee et al., 2017; Wang et al., 2018a). In addition to generating data, GANs can also be applied to data upsampling, data privacy protection, and data augmentation, as they excel in learning and reproducing the data distribution of the target dataset (Beaulieu-Jones et al., 2019; Litjens et al., 2019; Bowles et al., 2018; Quintana et al., 2020; Yan et al., 2020; Rachele et al., 2021; Wu and Biljecki, 2022).

The built environment hosts a large amount of data in different formats and on different scales. As GANs have been shown to be applicable to solving a variety of tasks, researchers have also begun to apply GANs to domain-specific problems in the built environment.

As this paper will demonstrate, GANs have been applied in more than 26 different domains of applications relevant to the built environment, from sharpening remote sensing images for urbanization studies (Pham and Bui, 2021; Bittner et al., 2019), to reconstructing neighborhood 3D models (Du et al., 2020; Kelly et al., 2018) and creating floor plans (Nauata et al., 2020; Uzun et al., 2020).

In this paper, we present a state-of-the-art systematic review of 100 studies on the application of GANs in the built environment on all scales and data types, covering novel ideas applied at the city, district, and building level. We provide an analysis of key GAN model architectures that are applicable in the built environment and a hierarchical organization of current subtopics that have been tackled by researchers in recent years. To the best of our knowledge, this is the most comprehensive and wide-ranging review on this topic. The review will inform readers about the state-of-the-art applications of GANs in the built environment and offers future research opportunities that push the boundaries of Artificial Intelligence in the urban context.

In Section 2, we examine existing related reviews, and Section 3 provides a primer on the architecture of GANs and introduces their capabilities to readers who are unfamiliar with this type of deep learning model. In Section 4, we describe our methodology for systematic review. Section 5 presents the quantitative and qualitative insights of the review with a meta-analysis. It breaks down the corpus by the problems addressed and the scale of the data from cities and districts to the building scale, and describes the applications of GANs in the built environment, focusing on three key topics, Data Synthesis, Data Augmentation, and Design Automation. Section 6 summarizes the key lessons learned and common limitations and outlines four research opportunities in the applications of GANs in the industry.

2. Related work

To our knowledge, there are three review papers that complement our work by looking at related topics from different perspectives.

Chaturvedi and de Vries (2021) provide an overview on the use of machine learning algorithms in urban land use planning. The review provides an overview of various machine learning approaches that are useful for modeling, simulating, and predicting urbanization patterns. A wide range of machine learning algorithms are covered, ranging from classical models like Random Forests to Deep Learning techniques like Convolutional Neural Networks. It briefly touches on the use of GANs in simulating urban growth as an alternative to procedural tools.

Gao et al. (2022) deliver a comprehensive systematic review of the application of GANs for spatiotemporal data. The review explores different forms of spatiotemporal information such as musical data, ECG and meteorological data, social network data, pedestrian trajectories, etc. Some of the datasets covered in the review are relevant to urban planning. For example, it shows that GANs can be applied to impute, augment, or generate pedestrian trajectory data, point of interest data, or traffic data for urban analytics.

Hughes et al. (2021) take a different route and explore how GANs could enable creative workflows that collaborate with human designers. The review reported different applications of GANs for the creative and design industries. One section features the application of GANs to help architects and urban planners generate floorplans and visualize the implications of land use decisions in real time.

Comapred to these previous work, our review focuses on a cross section that examines the application of GANs to all types of data that are applicable to the built environment. We specifically look at the application of GAN on all aspects in the industry, focusing on the breath of the application of GAN in the building environment.

3. Overview of GANs

As briefly covered in the Introduction, GANs are constructed with a generator network paired with a discriminator network. During forward propagation, the loss function calculates the difference between the generated sample and the ground truth. The loss is then backpropagated to the generator as feedback to improve the generated results (see Figure 1).

The very first GAN introduced by Goodfellow et al. (2014) is only capable of generating black-and-white facial images with some semblance of the original. After using more stable loss functions such as Wasserstein loss (Arjovsky et al., 2017) and optimal transport loss (Salimans et al., 2018) and deeper network layers such as convolutional layers (Radford et al., 2015), state-of-the-art GANs can now generate images indistinguishable from human perception.

GANs can be classified into two main categories: unconditional and conditional GANs. Unconditional GANs generate results based on randomly initiated noise vectors, giving users little control over the results they generate apart from

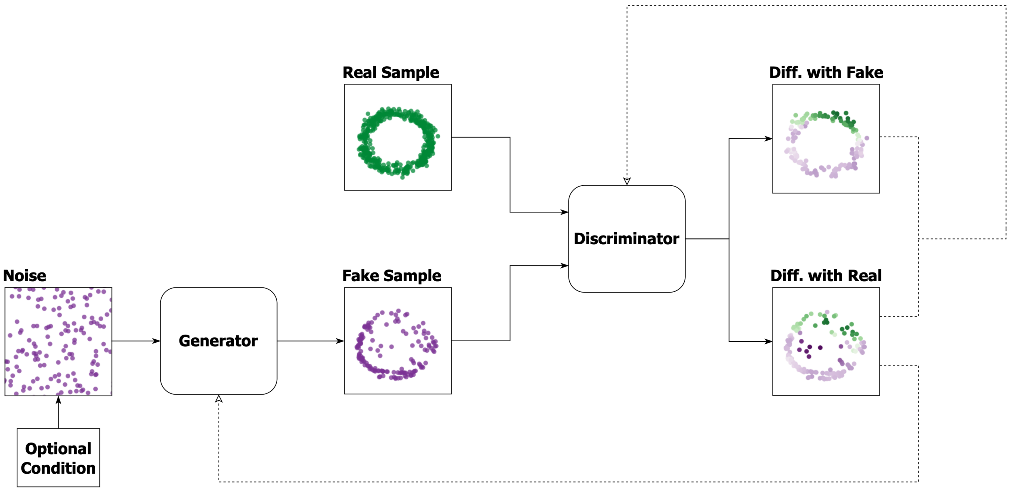

Figure 1: General architecture of a GAN. During forward propagation, random noise is passed into the generator to generate a fake sample (if a conditional vector is used, the GAN becomes a conditional GAN and the user can influence the outcome of the generator). The discriminator takes in both the real and fake samples to determine which is real. Then a loss gradient is calculated using a loss function, and the respective losses are back-propagated to the Generator and Discriminator. There is no restriction on the format of the real and fake samples, as long as the neural network architecture of the Generator and Discriminator adapts to the data formats.

tweaking the training dataset. Conditional GANs allow the user to input some additional information to 'guide' the model to generate the intended dataset, offering more granular control on the generated results.

There are multiple ways to customize a GAN to fit different generative tasks and different data formats. In general, every GAN is designed on the basis of its generative task and on its input-output data type. This is due to the fact that the generator and discriminator networks in a GAN require specialized deep learning layers to process different datatypes for the best results. For example, image generation GANs are often equipped with an autoencoder generator with convolution layers (Isola et al., 2017; Zhu et al., 2017; Park et al., 2019; Karras et al., 2019) to generate high-resolution RGB images. At the same time, the discriminator also needs convolution layers to assess the quality of the generated images. This type of model architecture will work only on image data but not on text data. Similarly, text-to-image GANs learn the relationship between input text and output images using generators with Attention layers or long-short-term memory layers (Xu et al., 2017) that could understand contextual information in input texts and discriminators with convolution layers to assess the difference between the generated images and the ground truth images.

Although GANs need to be designed for each input-output data pair, the applications that could arise from each data pair are manifold, as researchers could customize the information contained in the input-output datasets to apply the models to specific fields. For example, in their seminal paper, Isola et al. (2017) proposed an image-to-image translation algorithm that takes the semantic information defined in the input image and generates photorealistic images following the semantic information. The paper showcased the application of the algorithm to different data pairs, such as painting landscape photos with simple color-coded masks, coloring hand-drawn sketches, and inpainting missing pixels in images. Although each application is unique, the underlying datasets for all applications are still image pairs. The same model architecture has been used with only a few parameter tweaks that optimize the model for each data pair (see Figure 2). Another example is AttnGAN (Xu et al., 2017), which can synthesize semantically correct images from visual descriptions, learning the relationship between nouns and prepositions in natural languages. With it, architects had used it for design inspiration by translating poems into actual images for their design projects.

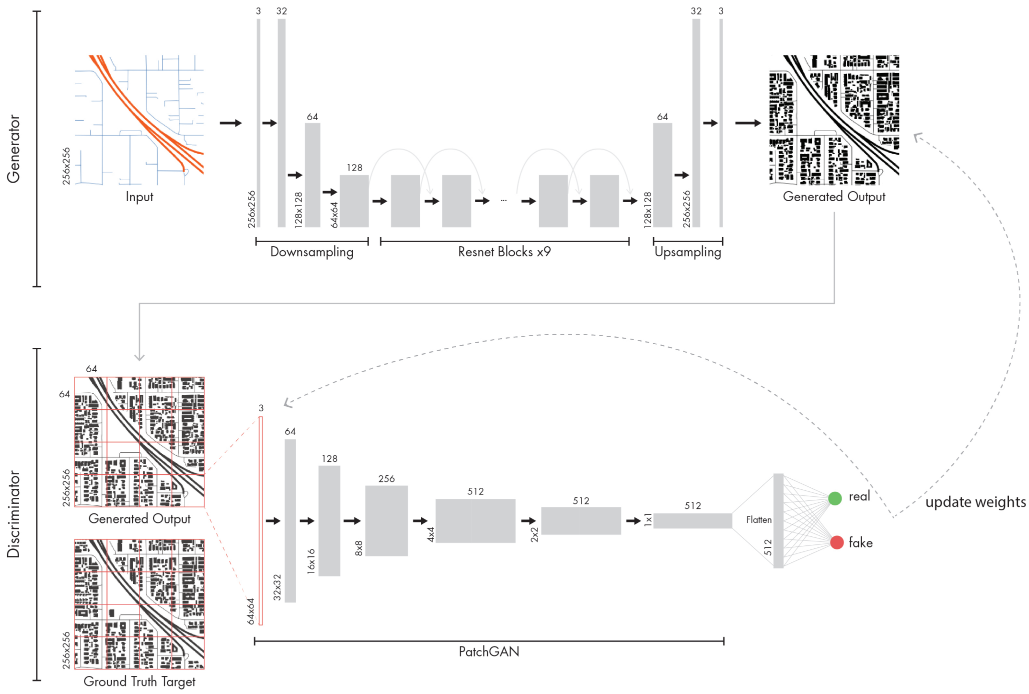

Figure 2: An example of a GAN for image-to-image translation using OpenStreetMap data. The generator and discriminator are optimized for image data generation and classification, respectively (Wu and Biljecki, 2022).

This information-agnostic trait has made GANs much more accessible to researchers outside the field of computer science, as more focus is on collecting domain-specific data, which leverages the domain expertise of researchers in other fields. Presently, the entry barrier to experimenting with GANs is made even lower, as many powerful GAN models tackling different tasks have been made open-source. This allowed researchers from fields outside of computer science to gain access to these models. In applying GANs to the built environment, researchers in the field have ridden the wave of these open-source repositories and designed spin-off models fine-tuned to the tasks specific to the industry. Notable open source repositories that are being used in the built environment include, but are not limited to, pix2pix (Isola et al., 2017), SEASAME (Park et al., 2019), CycleGAN (Zhu et al., 2017), StyleGAN (Karras et al., 2019, 2020), AttnGAN (Xu et al., 2017), and GraphGAN (Wang et al., 2017a).

4. Methodology

4.1. Overview and time frame

This systematic review was conducted based on the updated PRISMA guidelines (Page et al., 2021) to identify, select, and review studies. The initial pool of articles is identified using Scopus and Web of Science. Then we review the abstracts of these articles to assess their eligibility. The full text of the eligible papers is then examined in detail and relevant data is extracted for comparative analysis. We focus on papers from 2018 to 2021, since most papers on the application of GANs in the built environment start from 2018. A random sampling is conducted for papers before 2018 and there are no unique cases that are not already covered in the aforementioned period.

4.2. Search strategy

Figure 3 outlines the search and screening strategy. First, a pool of papers containing the relevant keywords ('Generative adversarial network' and 'GAN') are identified in their title, abstract, or keywords. This ensures a high diversity of papers that employ GANs in one way or another prior to further search.

Next, we applied topical keywords to sift out papers that address the built environment. The keywords are: '3d building', 'urbanization', 'urban design', 'urban planning', 'urban analysis', 'geospatial data', 'geographical data', 'street view', 'architectural design', and 'building design'. These keywords cover studies that span from the city scale to the building scale and different types of applications, from data processing to design automation.

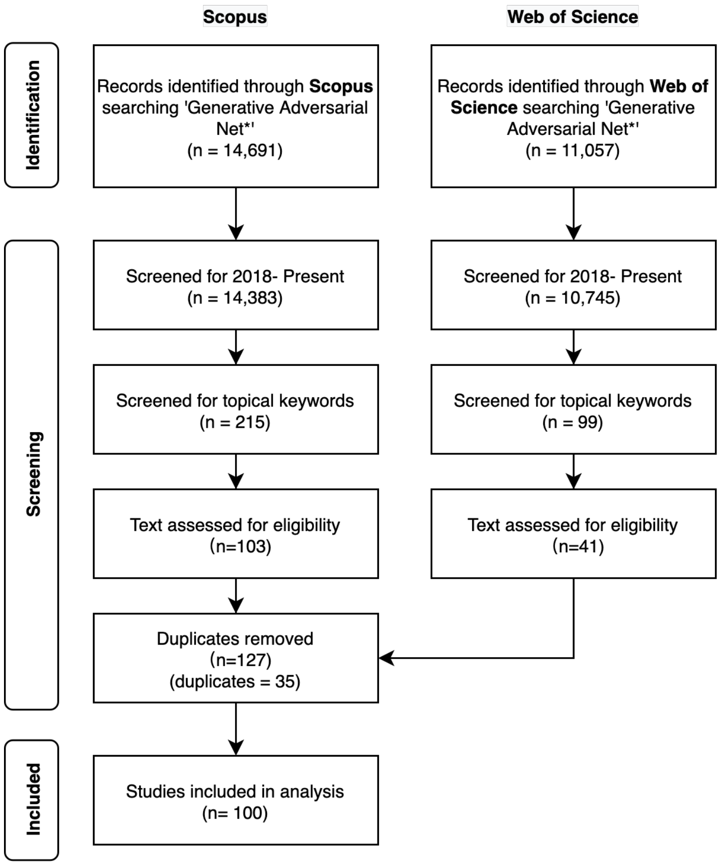

Figure 3: PRISMA flow diagram for literature selection.

4.3. Study selection and data extraction

After the search, we screened the abstracts of the articles in the initial pool to create a corpus of articles that are relevant for this review using the following criteria: (1) the study uses GANs to address problems in the built environment on the urban, district, or building scale; (2) the article is in English; and (3) the article describes the implementation of GANs using relevant data from the built environment and not a computer science paper that uses BE data such as satellite and street view images for metric computation.

Of the initial 314 studies identified using topical keywords, 100 articles have been selected for review. For each article, we extracted several metadata for a quantitative understanding of the body of literature in Section 5 (e.g., data format, GAN architecture, data size, application domain, and application scale).

As is the case with other systematic reviews, we acknowledge the possibility of exclusion of relevant articles during the search and screening process. Nevertheless, considering the large literature body and the multitude of application domains covered, we are confident that our review does not suffer from significant bias, is sufficiently covering the current trends of this domain, and presents a comprehensive and meticulous snapshot of the state-of-the-art.

5. Review

Here, we introduce the findings from the selected corpus in four subsections. We first classify the types of data based on the scale of the problems to be tackled. Then, we explain the popular GAN architectures used in the corpus and their respective data formats. Finally, we present an overview of applications of GANs in the built environment based on three thematic clusters.

5.1. Data types and scales in the Built Environment

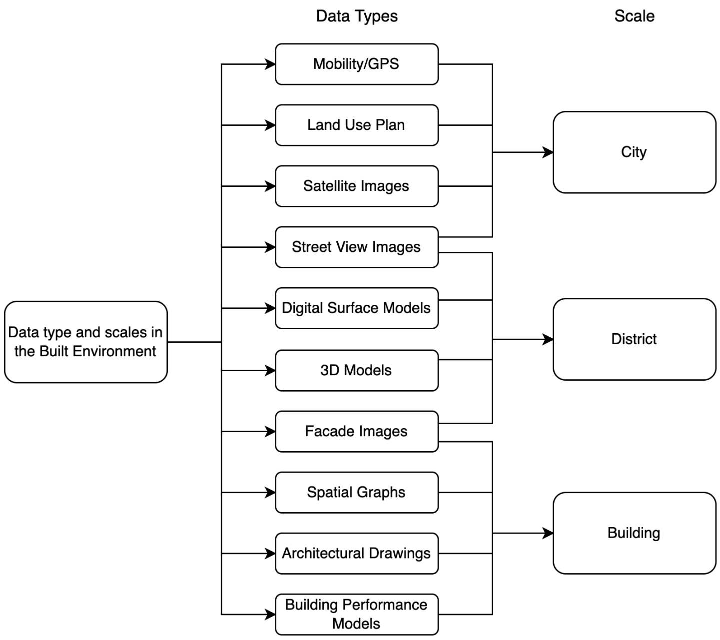

Figure 4: Data Types and Scales Used by GANs in the Built Environment.

The built environment houses a wide range of data types covering information at different scales. Data captured at one scale will only be most useful at the same scale where it is captured, therefore, it is crucial to connect the different data types to the scale that the data cover so that the best GAN methods can be selected for scale-sensitive tasks. Figure 4 shows the data types used in the training of GANs in the built environment. The ten data types can be classified into data at three scales, City, District, and Building. Most of the data types are scale-specific while street view images and facade images can be used across scales.

Data at City level. At the city level, researchers in the field mainly utilize remote sensing image datasets or spatio-temporal datasets to answer city-scale problems such as urban mobility simulation and urbanization growth prediction. Another focus at the city level is urban land use planning. Researchers have shown that GANs could learn existing land use design principles and apply them to new areas with sufficient design sensibility.

Data at the city scale are mostly large datasets ranging from 100k to 500k images or data points. With these data, common research questions include, but are not limited to: *Can we detect changes or simulate urbanization processes throughout the years (Albert et al., 2018; Chen et al., 2019; Hou et al., 2020)? Can we generate street view images from contextual information from satellite images (Deng et al., 2018; Tang et al., 2019; Regmi and Borji, 2018)? Can we create an AI that finds the best land use configuration (Wang et al., 2020)? Can we create a 3D representation of a city out of 2D images (Kim et al., 2020; Bittner and Korner, 2018; Kelly et al., 2018)? Can we estimate or impute missing structured data to aid downstream analysis (Yang et al., 2021; Zhang et al., 2019b; Johnsen et al., 2021)?*

Data at District level. The district level refers to studies focusing on neighborhoods or a few urban blocks. At this level, data that contain information on urban fabric become more prominent. However, the sizes of the datasets are generally much smaller than those at the city level, ranging from one thousand to fifty thousand.

At this level, street view images are being used to quantify spatial quality by feature extraction, and researchers are attempting to use GANs to redesign streetscapes with better spatial quality. At the same time, building facade images and 3D models are also being used in GANs for novel ways to reconstruct urban districts, rivaling the performance of procedural approaches.

Common research questions on this scale include, but are not limited to: *Can GANs be used for effective 3D urban reconstruction (Kelly et al., 2018; Du et al., 2020)? Can we interpolate the urban fabric from one area to another (Yao et al., 2021; Shen et al., 2020; Wu and Biljecki, 2022)? Can AI assist human designers in masterplanning (Ye et al., 2021)?*

Data at Building level. At the building level, architectural drawings such as floorplans, mechanical, electrical, and plumbing (MEP) drawings, and sectional drawings are widely experimented with. Researchers have shown that GANs could generate sensible technical drawings and help with plan coloring. Certain GAN processes can also act as a design interpreter, translating hand sketches into colored architectural renderings. More recently, researchers have started exploring how to represent the spatial arrangements of these drawings in graphs instead of images, allowing GANs to learn spatial correlations between different spaces in a building.

In addition to these data, photos of buildings such as artistic renderings and facade images have also been used for style classification and damage restoration. A smaller set of articles focus on building performance data, increasing the accuracy of building performance prediction with GANs (Chokwitthaya et al., 2020, 2019).

In general, datasets at the building level are more heterogeneous and context-specific, making the collection of a set of similar data much more difficult. Nevertheless, GANs still proved useful in these relatively smaller datasets and introduced creative and innovative solutions at the building level.

Common research questions on this scale include, but are not limited to: *Can AI generate architectural drawings that are spatially optimized (Uzun et al., 2020; Nauata et al., 2020, 2021)? Can AI restore old building facades in disrepair (Zhao et al., 2020; Zhang et al., 2018)? Can GANs generate design inspiration for architects and planners (Chen and Stouffs, 2021; Huang et al., 2021)?*

5.2. Data sources and availability

GANs are data-hungry deep learning algorithms that require a large amount of computation resources to reach optimum convergence and realistic results. As explained above, problems in the built environment are scale-specific, and GANs designed for the problems require data collected at the intended scale to be most effective.

Half of the articles in the review reported using an external dataset obtained from public databases. Table 1 shows a summary of these datasets used in the corpus. Most of the datasets are created to benchmark deep learning model performance to advance relevant research rapidly and are available for direct download. Although generally used in the field of Computer Vision, these datasets contain relevant information in the built environment across different scales. Data obtained from service platforms such as OpenStreetMap and Google Street View require API access, and the quota for academic use varies by platform.

The other half of the corpus used datasets that were generated independently by the researchers. These datasets might be curated from online sources such

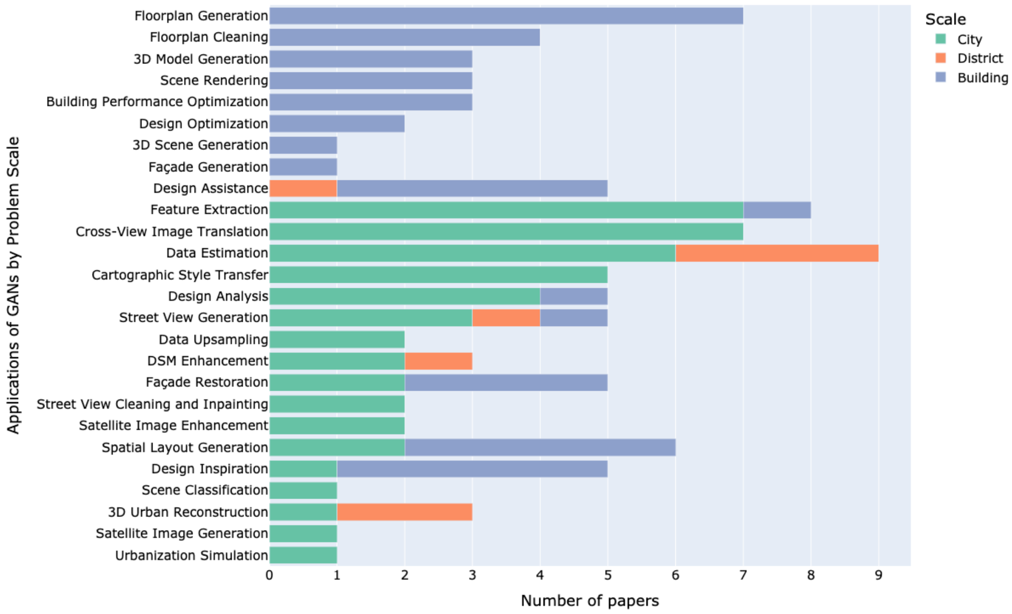

Figure 5: Histogram of GAN applications by problem scale.

as ArchDaily or Pinterest, or are provided by government organizations for the specific study. Some researchers also generated datasets by taking actual photos with cameras.

In addition to data access, data size is also an important factor in the training of GANs. Of the 100 papers in the corpus, 71 have reported the size of the datasets used in the research. Figure 6 presents a histogram on the size of the datasets used in the corpus on three different scales. We see that at the city level, the size of the dataset spans from hundreds to millions. The extremely large datasets are movement trajectory datasets which contain spatio-temporal data of thousands of tracking points over a long span of time. At the building level, smaller datasets are more common, since those are generally images of building facades or floorplans collected manually by the researchers.

5.2.1. *GAN variants for the Built Environment*

Although noticeable progress has been made in the application of GANs in the domain, there is no standardized naming convention for the GANs used in the papers. In some cases, researchers give a new name to their GAN model after tweaking certain parameters in a stock model (Liao et al., 2021) or after

Table 1: Publicly accessible datasets by coverage.

Coverage	Source	Format	Size	Cited
City	Baidu Street View	Street View	variable	1
	CVUSA	Street/Satellite	30k+	2
	CartoDB	Maps/Satellite	variable	1
	Cityscapes	Street View	20K+	2
	Dayton	Street/Satellite	70K+	2
	Ego2Top	Cross View Video	230	1
	GADM	GIS Data	29K+	1
	Google Street View	Street View	variable	4
	Google Maps	Maps/Satellite	variable	3
	Road damage	Street View	1500	1
	Grab-Posisi	GPS	8m+	1
	HERE Map	Raster Maps	variable	1
	OpenStreetMap	GIS Data	variable	1
	Paris Street View	Street View	50k+	5
	Massachusetts	Satellite	1500+	3
District	ADE20K	Photos	27K+	2
	BDD100K	Photos	100K+	1
	Microsoft COCO	Photos	160k+	2
	Places2	Photos	10m+	1
	PASCAL VOC	Photos	10k+	1
Building	EAIS	Floorplans	300+	3
	LIFULL HOME	Floorplans	100k+	2
	ROBIN	Sketches	200	1
	ZSCVFP	Vector Floorplans	10k+	2
	lianjia.com	Floorplans	100+	1

applying stock models to a customized pipeline (Chan and Spaeth, 2020). In other cases, the researchers did not refer their method to existing repositories, but the architecture implemented was similar to open source repositories (Kim et al., 2018).

This non-standardized nomenclature could be confusing to readers new to the field and make cross-referencing between relevant studies difficult. To clear up the confusion, we have classified the method nomenclatures found in the corpus by input-output data pairs. There are a total of 4 categories based on our

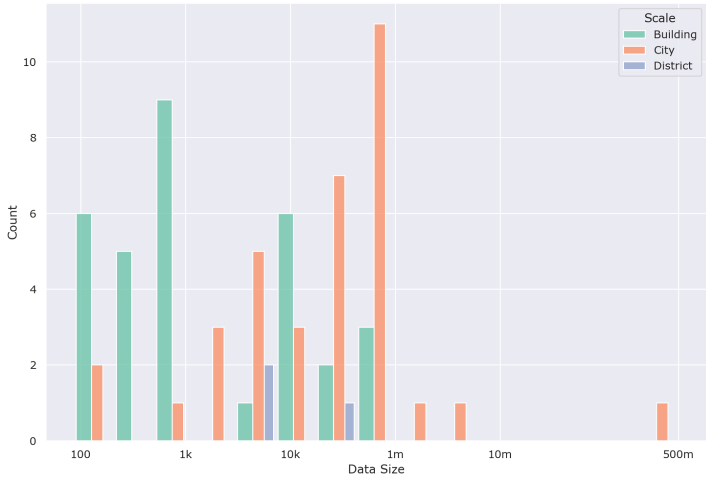

Figure 6: Dataset size used by GANs in the Built Environment group by data scales.

taxonomy, and Figure 7 shows the distribution of different GAN classes used in different thematic clusters documented in this study.

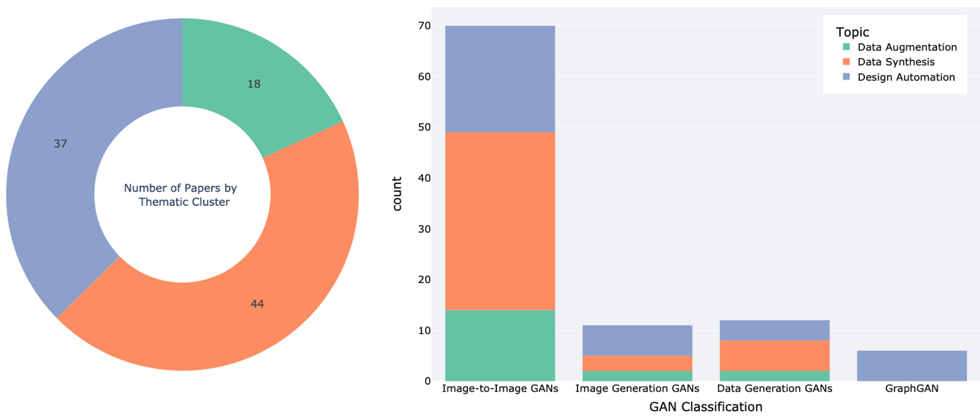

Figure 7: Number of papers under each GAN classification and thematic cluster.

Image Generation GANs GANs excel at image generation. Image Generation GANs are unconditional GANs with deep learning layers that generate photorealistic images from input noise vectors, and generally have more complex architectures than Data Generation GANs mentioned below. When GAN was first introduced by Goodfellow et al. (2014), the images generated were of low resolution. Adding deep convolution layers to the vanilla GAN architecture, Radford et al. (2015) managed to generate higher resolution and colored images of human faces. Research in Image Generation GANs continued with more stabilized training processes (Roth et al., 2017), new generative algorithms (Karras et al., 2019, 2020), and better semantic accuracy (Karras et al., 2021).

StyleGAN3, the current state-of-the-art in this domain, is able to generate hyperrealistic high resolution images of human faces, animals, landscape, and street view images. Another branch of applications of Image Generation GANs is in image inpainting. Rather than generating images from randomly initiated vectors, image-inpainting GANs help to complete missing pixels or restore blurry patches in an image taking information from the surrounding context. Notable GANs that are used in the corpus include UCTGAN and DeepFill (Zhao et al., 2020; Yu et al., 2018).

Data Generation GANs Data Generation GANs are conditional or unconditional GANs that could generate data other than images. Data such as text, GPS, and mobility data can be processed by these GANs to generate new data samples that are similar to the ground truth, and papers in the corpus use this type of GANs to generate more data samples for better downstream learning. In addition, these GANs can be used to translate one dataset into another, and the combination of the input-output pairs does not need to be of the same data format. For example, AttnGAN (Xu et al., 2017) uses attention layers for text understanding and then uses a deep convolutional neural network to generate images from decoded text. TrafficGAN (Zhang et al., 2019b) uses conditional vectors to encode traffic demands and generates spatial-temporal datasets of traffic conditons based on the demands.

Image-to-Image GANs One of the most popular uses of GANs is in image-to-image translation. This type of GANs can translate one kind of image data into another. In most use cases, it is used to translate segmentation masks into photorealistic images. For example, generating realistic street view images from color-coded street object labels or picturesque scenery from color masks that indicate object types. This application was first published by Isola et al. (2017) as 'pix2pix' and was further improved in pix2pixHD (Wang et al., 2018c), SPADE (Park et al., 2019), and SESAME (Ntavelis et al., 2020). One limitation of the pix2pix family of GANs is that each training sample needs to be a set of paired images. As GANs are data hungry, training datasets could easily exceed tens of thousands of image pairs. In problems where the pairing of the training samples could not be automated, a large amount of human labor is required to generate a suitable dataset for training. To solve this limitation, CycleGAN introduced Cycle-consistent loss (Creswell et al., 2018), which enables unpaired image translation. CycleGAN no longer requires paired samples during training and learns to translate between two image datasets from all images. This feature significantly speeds up data preparation, making CycleGAN experiments much more scalable in tasks that lack paired datasets.

GraphGANs GraphGANs are GANs that are capable of using graph data as input or generating graphs as output. Graphs are a type of unstructured data that can describe topological data with nodes and edges. In the built environment, researchers are starting to use graphs to describe spatial relationships at different scales (e.g. road networks at the city level, floorplan layouts at the building level). Compared to recording these data in images and structured data, graphs allow GANs to generate more spatially sensible results (Nauata et al., 2020).

5.3. Applications of GANs in thematic clusters

In this section, we discuss common research topics that have been addressed by GANs in the built environment. Upon examining all the papers, we developed a two-tier system to classify the papers meaningfully. We first classify the studies into three main generative tasks based on how the generated samples from the GAN model are used.

1. A task is classified as Data Synthesis if the output data format or nature is different from the input, and can be used qualitatively and quantitatively for downstream workflows.
2. A task is classified as Data Augmentation if the output is similar to the input, but of a higher quality in resolution or completion, and can be used qualitatively and quantitatively for downstream workflows.
3. A task is classified as Design Automation if the output data format or nature is different from the input and cannot be used quantitatively for downstream processes. However, the output provides qualitative value that inspires or automates certain processes during a workflow.

Then, each paper under these three tasks is further differentiated by their respective application domains. There are a total of 26 application domains in the three generative tasks. We hope that this taxonomy is helpful to readers in navigating the wide landscape of current applications (see Figure 5 and Figure 8).

5.3.1. Data Synthesis

Data synthesis refers to applications where GANs are used to generate synthetic results that can be used both qualitatively and quantitatively.

3D Urban Reconstruction Kim et al. (2020) used GANs in their 3D city model generation pipeline to generate terrain maps from semantic masks of street

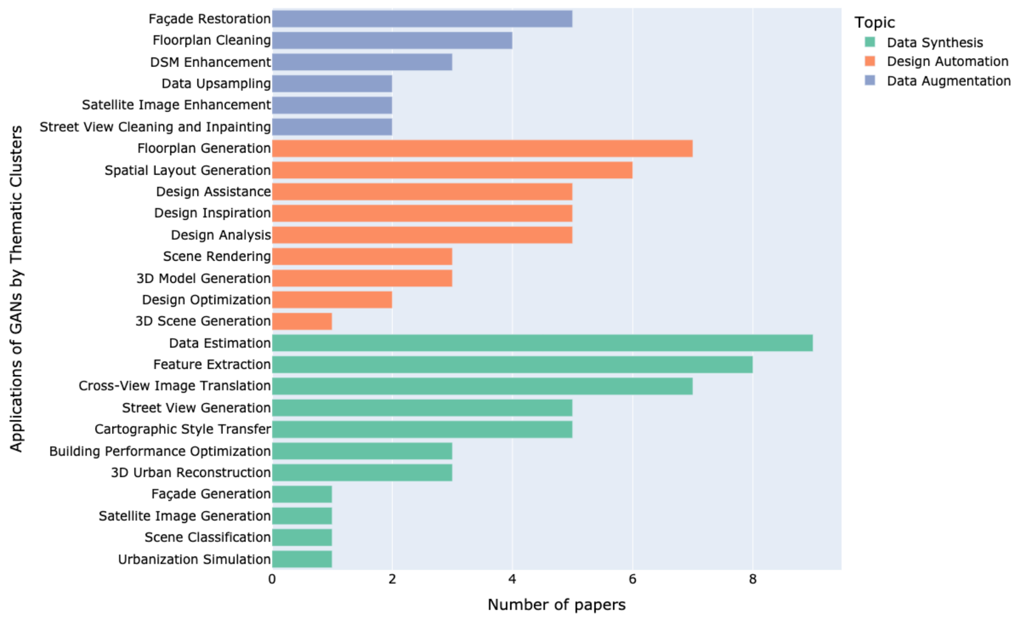

Figure 8: Number of papers under each theme and application.

views. The terrain map is combined with property vectors extracted with a Convolutional Neural Network from RGB street view images to automatically create a realistic 3D city model.

The methods proposed by Kelly et al. (2018) and Du et al. (2020) focus more on improving the level of detail of the generated 3D models (see Figure 9). In both studies, multiple GANs are linked to generate texture and label maps for facades, roofs, and windows. The method of Kelly et al. (2018) also uses a super-resolution process to enhance the resolution of the generated texture. Using the textures and label maps, 3D details are added to the input level of detail 1 3D model, making the model much more lifelike. Additionally, style preferences can be set in the pipeline to give users greater control over the final results.

Building Performance Simulation/Optimization Building performance modeling is important in understanding the thermal and daylight comfort of a building. However, existing building performance models only describe historical events and observations, and contextual factors that influence human-building interactions, such as the decision to switch on and off interior lighting and ventilation, are ignored. Using GANs, Chokwitthaya et al. (2019, 2020) can generate synthetic datasets to estimate the effect of building performance on human deci-

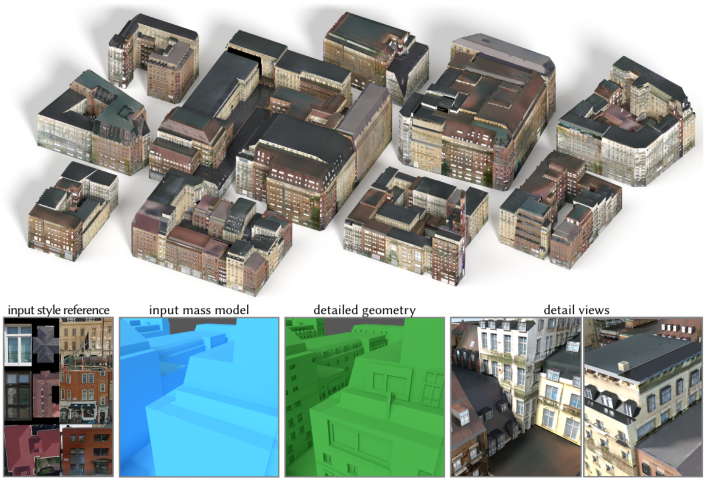

Figure 9: FrankenGAN by Kelly et al. (2018).

sions and vice versa. Also on the topic of building performance, He et al. (2021) show that GANs are effective metamodels for daylight simulation, achieving R-square score of 0.959 when compared against state-of-the-art daylight simulation tools.

Cross-View Image Translation Cross-view refers to the method to generate images with drastically different views, such as street view images from satellite images and vice versa. This task is challenging because understanding, corresponding, and transforming the appearance and semantic information across views is a complex computational problem (see Figure 10).

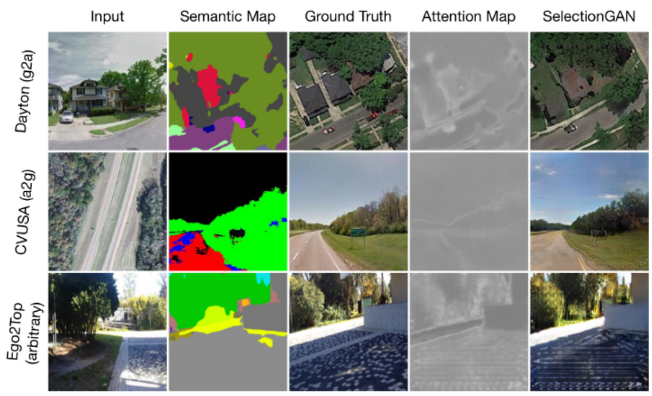

Figure 10: SelectionGAN by Tang et al. (2019).

When training a vanilla pix2pix model on these datasets, the results often suffer from blurred patches and semantically incorrect objects. Using more advanced GAN architectures, such as those based on customized convolution layers (X-Fork, X-Seq) (Deng et al., 2018; Regmi and Borji, 2018, 2019), attention layers (SelectionGAN) (Tang et al., 2019; Ding et al., 2020), or Cycle-consistent losses, (Tang et al., 2020a) researchers are now able to translate between satellite and street view images with accurate semantic structure and in high resolution.

The state-of-the-art models are achieved using large datasets that contain street view and satellite image pairs (Dayton, CVUSA, and Ego2Top). These datasets range from 30k image pairs to 50k image pairs and have greatly accelerated research in this field.

Data Estimation and Urban Simulation Data Estimation refers to the various applications of using GANs to predict missing data using contextual information obtained from the training dataset. In many applications, GANs can learn the complexities of the training data and reproduce similar data patterns when given a new condition. For example, Zhang et al. (2019b, 2020b) have created a method to estimate traffic condition changes of a region prior to deployment to aid city planners to evaluate the impact of different traffic design schemes. TrafficGAN used a large taxi inflow dataset to learn the fundamental patterns of how traffic conditions evolve with changes in travel demand and the underlying structure of the road network. The generator is able to generate realistic traffic conditions given not-yet-observed travel demand. Furthermore, the performance of TrafficGAN outperforms existing traffic estimation techniques.

Another example of using the power of GANs in data estimation is to simulate population density and distribution on all scales of the built environment. Zhang et al. (2020a) used call detail records of mobile phones to forecast accurate population density up to a spatial resolution of 125 x 125 square meters over different time periods. Furthermore, Johnsen et al. (2021) used GAN to estimate the demographic profile (e.g., type and composition of households, income, and social demographics) of urban residents in new neighborhood developments to measure the social impacts of new real estate developments.

Data estimation can also be applied to image data. Zhu et al. (2020a) used an image conditional GAN to estimate terrain data, which outperformed traditional interpolation techniques, and Shen et al. (2020) have shown that a pix2pix model can be used to transfer urban morphology from one place to another. Yao et al. (2021) built on this technique to generate neighborhood footprints at different densities of the surrounding urban fabric.

At the city scale, Albert et al. (2018) are among the first to apply conditional GANs to simulate urbanization patterns under different conditions in cities. More recently, Ibrahim et al. used a GAN to estimate future housing growth patterns for different demographic groups in Doha, offering a new data-driven method for population and urbanization simulation. Additionally, Sun et al. (2021a) are able to predict the future land use and land cover change of Shenzhen in the future by learning from historical urbanization patterns from 1988 to 2015.

Façade, Satellite and Street View Generation One of the most popular uses of GANs is in the generation of photorealistic images. Researchers in the Built Environment have stress-tested image generation GANs with different types of domain-specific datasets. Using CycleGAN with a self-curated historical architecture dataset, Sun et al. (2022) trained a model that generates traditional building facades from semantic masks with customized decoration styles. This method could be scaled up to a city-wide platform that can automatically provide urban restoration options from the aspect of architectural heritage conservation.

In addition to building facades, street view images and satellite images can also be generated from semantic guidance or randomized noise vectors. Due to the availability of large datasets of street view and satellite images, many image generation GANs used these datasets as benchmarks (cite pix2pixHD, GauGAN). For example, using StyleGAN, an open source image generation GAN, Steinfeld (2019) generated a walk-through video of a fictional neighborhood stitched from a series of spatially continuous synthetic images. (Zhao et al., 2021a) have also generated high-resolution satellite images with StyleGAN and warned about the danger of data contamination and malicious use of such images as untrained eyes are now unable to distinguish the real from the fake. In the research of Wang et al. (2019a) and Venator et al. (2021), lighting conditions (i.e. day and night) can also be varied in addition to image semantics to generate street view images based on different times of the day.

To push the boundary further, researchers have designed GANs with components that specifically improve semantic guided street view generation. Tang et al. (2020b) created a GAN with three generation branches, that is, global image level generation, local class level generation, and pixel level fusion weight map generation. The result of LGGAN is superior to general models such as SPADE in semantic street view generation and also in cross-view image translation. Zhu et al. (2020b) also introduced a customized GAN based on semantic region-adaptive normalization that can achieve superior results in street view generation. Furthermore, the method can also be used to generate interior scenes.

Cartographic Style Transfer Maps are an important visual medium that conveys information about a city and district. Inspired by the technique of style transfer in image editing, researchers can take two cartographic images, a content image and a style reference image (one with a different style than the content), and blend them together so that the generated map retains the information in the content map, but "painted" in the style of the style reference map. Using GANs, researchers have converted simple styled maps captured from OpenStreetMap into the style of Google Map (Kang et al., 2019) or historical maps. It is also possible to convert Google Map and other mapping styles into satellite images and vice versa using CycleGAN and pix2pix (Xu and Zhao, 2018; Zhang et al., 2020c; Li et al., 2020).

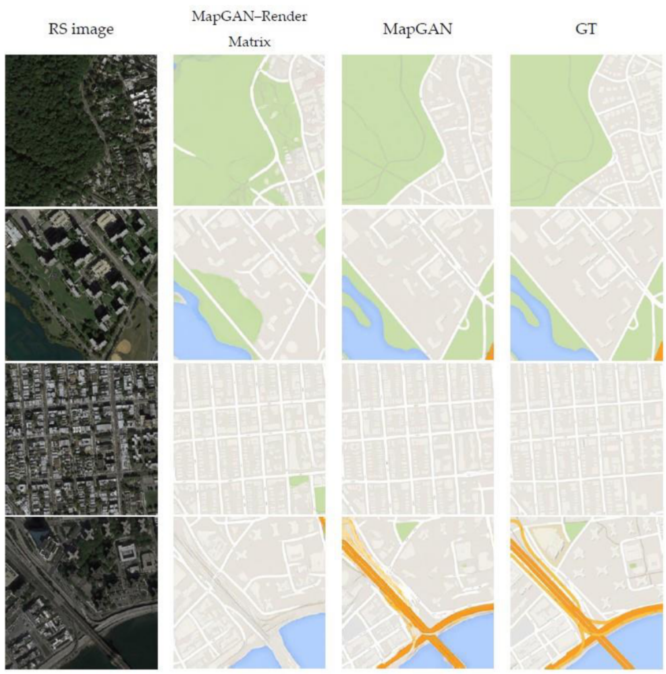

Figure 11: MapGAN by Li et al. (2020).

Semantic Segmentation and Change Detection Semantic segmentation is the task of clustering the pixels of an image that belong to the same object class. It is a form of pixel-level prediction, since each pixel in an image is classified according to a category. Semantic segmentation is particularly useful in describing and quantifying the information contained in images. It unlocks a wealth of data as quantifiable data can now be extracted from photos taken at any scale, accelerating our understanding of the built environment through satellite, street view, and building images.

As GANs could generate images from semantic masks, the process can be reserved to train GANs to generate semantic masks from RGB images as well. The most popular model used in this task is pix2pix, followed by CycleGAN. Researchers in the field have applied this process on road networks at the city level (Shi et al., 2017; Varia et al., 2019), building footprints at the district level (Wu et al., 2018; Abdollahi et al., 2020; Sun et al., 2021b), and architectural elements such as windows, doors, and walls at the building level (Alawadhi and Yan, 2021). One notable application of the extracted semantic masks is in change detection. Chen et al. (2019) and Hou et al. (2020) create pipelines to detect and quantify urbanization changes over the years by extracting semantic information from time series remote sensing images.

5.3.2. Data Augmentation

Compared to data synthesis, data augmentation refers to processes in which GANs are used to enhance input data by cleaning, restoring and increasing resolution. Applications of these are mostly used as an intermediate step to help the final output.

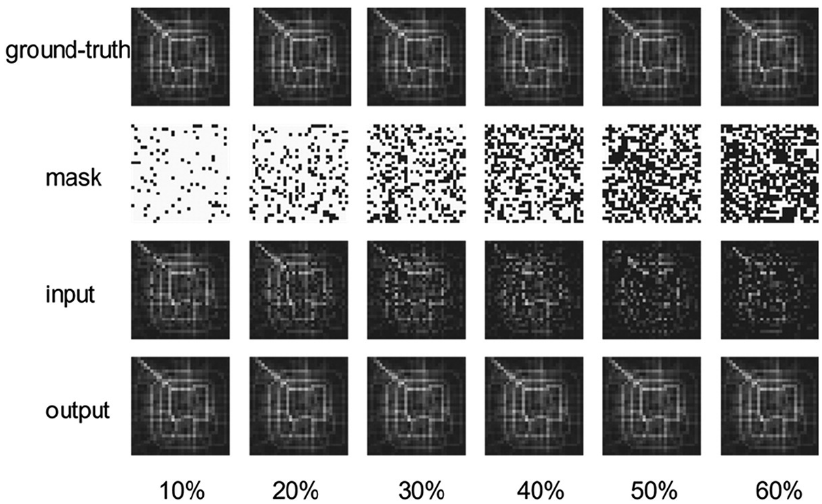

Figure 12: ST-FVGAN by Yang et al. (2021). The percentage represents how much data was removed from the ground truth as input for the upsampling process.

Data Upsampling In urban big data problems such as traffic condition monitoring, the collected data may have missing values that would impact the analysis result. To overcome this limitation, Yang et al. (2021) created ST-FVGAN to impute missing time series traffic data (see Figure 12). The GAN is capable of considering the spatiotemporal correlation between different data points and is more accurate than traditional imputation methods. Furthermore, Wang et al. (2018b) used a GAN to up-sample Sina Weibo microblog comments, generating synthetic text examples to augment the existing dataset for better downstream prediction of traffic conditions using natural language processing models.

Facade Restoration Facade Restoration studies the possibility of restoring missing pixels in facade images from contextual information given in the input. Many researchers have proposed different GAN architectures that can be used to fill in missing information in an image with semantic consistency (Zhang et al., 2018; Li et al., 2019; Zhao et al., 2020; Liu et al., 2021; Qin et al., 2018). In some cases, a building with more than 50% missing pixels could still be restored with realistic elements.

Satellite Image Enhancement Satellite images are useful in large-scale urbanization studies. However, high-quality satellite images are expensive, and open-source datasets often suffer from quality issues such as low resolution and the presence of clouds.

Using a GAN-based model, Pham and Bui (2021) created a method to increase the spatial resolution of freely available Landsat imagery with four reflectance bands (red, green, blue, near-infrared) and the panchromatic band. The output images have higher spatial resolution and are more spatially convincing. This enhanced dataset allowed researchers to access historic satellite images in high definition and thus allowed studies over time.

Ikeno et al. (2021) has shown that GANs can be used to remove clouds from satellite images and make building footprints beneath the clouds much more visible for a downstream building footprint segmentation model. By using GANs to augment the training data for the downstream model, the mean intersection over union (mIoU) score improved from 0.622 to 0.651.

Digital Surface Model Enhancement Digital Surface Models (DSM) contain terrain elevation information that can be used in automatic urban 3D reconstruction. However, accurate 3D information extraction requires high-resolution DSMs scanned using expensive airborne laser scanners (Pang and Biljecki, 2022). A group of researchers managed to reduce the cost of obtaining high-resolution DSMs by enhancing the resolution of more readily available low-res DSMs generated from stereo satellite images by using a GAN based on pix2pix (Bittner and Korner, 2018; Bittner et al., 2019). The output result greatly improves from the low-res stereo DSMs and closely matches the DSMs collected through airborne lasers. Wang et al. (2021) took one step further to generate fully vectorized level of detail 2 building models from enhanced DSMs and achieved state-of-the-art performance when applied city-wide (see Figure 13).

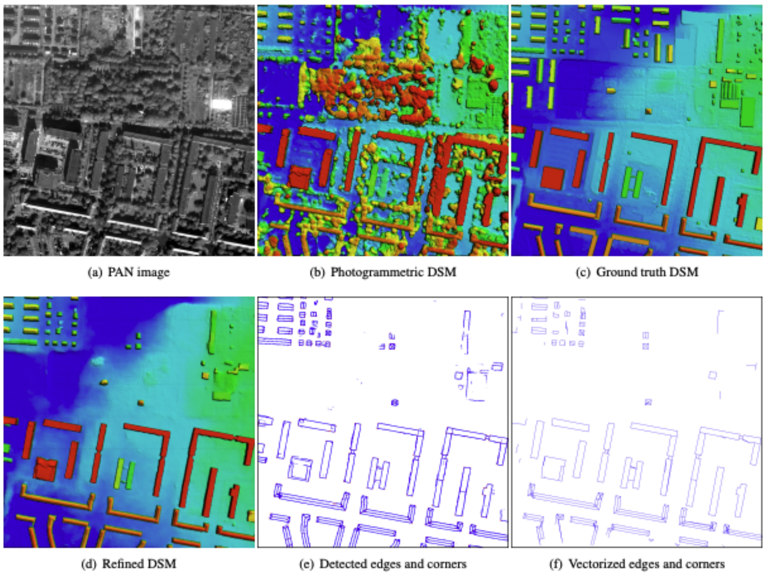

Figure 13: Enhancement and vectorization of digital surface models using GAN by Wang et al. (2021).

Street View Cleaning and Inpainting Similar to clouds in satellite images, street view images also face quality problems, such as obstructed views and rains. Hettiarachchi et al. (2021) show that GANs can effectively remove rain streaks from street views to improve image clarity. This means that street view recording can continue in the rain without deteriorating the quality. Zhang et al. (2021) has combined object detection algorithms with GANs for image inpainting to create a novel pipeline that removes road obstructions and subsequently repairs empty pixels using contextual information in the background. This enables highly accurate reconstruction of areas blocked by unwanted objects, such as a tree canopy or street signs, enhancing the quality of the data for downstream operations (see Figure 14).

Floorplan Cleaning Floorplans contain spatial and structural information of buildings. In practice, floorplans have many annotations to help human understanding. However, these annotations are a hindrance to machine understanding. One research direction in helping machines read floorplans is to encode raster floorplans into vector representations. To this end, researchers have developed GANs that detect building elements, such as walls, doors, and windows from complicated floorplans and convert them into a unified style for downstream machine learning. These algorithms are usually image-to-image GANs based on

Figure 14: Automatic object removal and inpainting by Zhang et al. (2021).

pix2pix and are enhanced with a subsequent vectorization algorithm to return vectorized floorplans in labeled primitives (Kim et al., 2018, 2021; Cho et al., 2020; Dong et al., 2021).

5.3.3. Design Automation

Design Automation refers to applications where GANs are used to generate synthetic results that could aid designers and planners in the design process. The results could provide inspiration for design or speed up decision-making and production processes.

3D Model/Scene Generation In the industry, floorplans and sectional drawings are used to describe the details of a project. Together, they contain information required for constructions in the 3D space. Using a similar idea, Zhang and Blasetti (2020) generated multiple floorplans and sectional drawings using StyleGAN and CycleGAN to construct 3D models inspired by modern architecture and Gothic churches. Taking another approach, Yu (2020) used pix2pix to generate color-coded masks as a more machine-readable version of floorplans and sectional drawings to reconstruct and redesign the spatial layout of a neighborhood and construct a 3D model from the masks using a similar concatenation technique.

In interior design, 3D artistic renderings are populated with furnishings and decor to convey different design styles. Currently, designers need to manually modify the textures of each object in a rendered scene to convert them into different styles. Zhang et al. (2019a) created a GAN to automate this process and modify the textures of 3D furniture models based on stylistic expressions learned from a real image dataset. To enhance the realism of the scenes, the method can also populate different interior decors such as plants, magazines, and photo frames that suit the chosen style. Furthermore, the GAN can also mix between different styles, generating new styles and color schemes that are not yet seen in the training dataset.

Design Analysis Researchers have also explored using GANs to analyze data to help architects and planners in preliminary studies.

For example, Wang et al. (2019b) used InfoGAN to classify and quantify street architecture styles in an unsupervised manner without needing prior manual labeling data. Since the model is not trained with labeled data, planners could use it to identify new classes that might not have been representative under human-directed classification.

In urban planning, data on how existing neighborhood characteristics impact resident behavior could help planners understand the effectiveness of design schemes. However, these data are limited in availability and spatial quality indicators (e.g., greenery, building setbacks, and dwelling structure) and are also difficult to quantify. Combining unsupervised classification of images with survey data, Rachele et al. (2021), Zhao et al. (2019), and Wijnands et al. (2019) are able to quantify the relationship of neighborhood characteristics with resident health and behavioral data, and elements of the streetscape with data on urban cyclist safety. Furthermore, the relationship learned by AI can be used to suggest better design solutions, as latent vectors that represent different elements (e.g., vegetation heights, vegetation density, and building density) can be adjusted to generate new images that suggest better spatial designs for specific functional spaces learned by the models.

In addition to images, GANs can also be used to perform spatial behavior analysis. Wang and Huang (2019) conducted a case study where Space Syntax is used together with a GAN to simulate pedestrian movement dynamics and identify crowded hot spots in a commercial area.

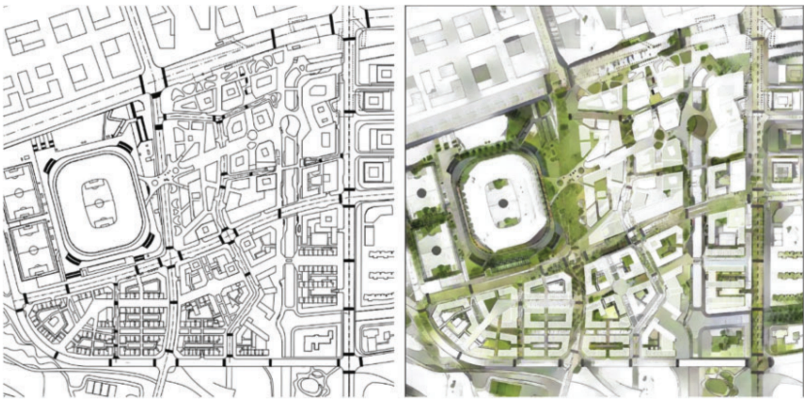

Figure 15: Automated coloring of Masterplans by Ye et al. (2021).

Design Assistance Design Assistance refers to automation processes that can speed up certain tasks in a designer's workflow. Qian et al. (2021) experimented with GANs to generate hand sketches from architectural photography. Using a similar algorithm, Sharma et al. (2019) created a method to retrieve CAD floor plans from hand-drawn sketches.

Ye et al. (2021) trained a custom GAN architecture with 5,000 masterplan images to colorize masterplan drawings. The results are judged to be aesthetically similar to manual renderings after 3450 unique pairwise comparisons by 150 survey participants (see Figure 15). At the building scale, Chan and Spaeth (2020) created a method to generate water-color building sketches from line drawings. The model can also be used to generate photorealistic renderings from colored sketches.

Navarro-Mateu et al. (2021) attempted to train a conditional GAN that generates 3D massing models based on two-dimensional color grids with different colors hinting at different massing types (eg. empty, block with windows, block with sloped roofs).

Design Inspiration Just like creating artworks using GANs, some designers have used GANs in design speculation, using generated images from GANs directly in their work or obtaining design cues from the results. Danchenko (2021) used StyleGAN to rapidly generate different architectural renderings for clients before engaging in manual design, speeding up the early ideation stage with AI-generated mood boards. Pasquero and Poletto (2020) used a CycleGAN to learn the growth pattern of Physarum polycephalum, a unicellular organism with computational abilities and self-organizing behavior. The GAN simulates the growth logic of the organism and is deployed to test the potential of non-human intelligence in solving problems of urban remetabolization and in computing scenarios of urban morphogenesis.

Campo (2021) used AttnGAN, a GAN that interprets text into images, to generate materials and color patterns for the design of a school. Text descriptions of activities conducted in functional spaces (e.g. multipurpose hall, classrooms) are translated into abstract images. These images are then reinterpreted and mapped to the respective buildings to complete the design.

Chen and Stouffs (2021) used StyleGAN2 to generate photorealistic building renderings from a large dataset collected from ArchDaily and Dezeen. The latent vectors within the trained model were modified to influence the model output in the intended direction. Huang et al. (2021) used architectural imagery generated by a DCGAN as visual guides for designers to generate elevation drawings. In this experiment, AI dictates the design direction and human designers fulfill the instructions. Key elements of the generated image are interpreted by architects as architectural elements, and four different elevations are combined into a 3D model inspired by the images hallucinated by GANs.

Design Optimization In an architecture project, architects must engage engineers to ensure the feasibility of the design. Liao et al. (2021) created StructGAN, a method based on pix2pixHD to indicate the position of structural walls in a floorplan of high-rise residential buildings. It is also able to propose the location suitable for windows and outdoor gates. After consulting a professional panel, the generated structural plans come close to expert design and can provide quick preliminary structural design schemes for architects and structural engineers, improving the design efficiency and quality of building structures.

Also using pix2pix, Sato et al. (2020) created a GAN that could generate the layout of the fire extinguishing system (FE) from the input floorplans. Using a metric that calculates the coverage of the FE system, the FE plans produced were close to the original FE designs. Furthermore, the system produces the output in 45 seconds, which is drastically faster than the conventional manual workflow. The system realizes the prompt engineering study learned from past as-built information, which contributes to data-driven decision making.

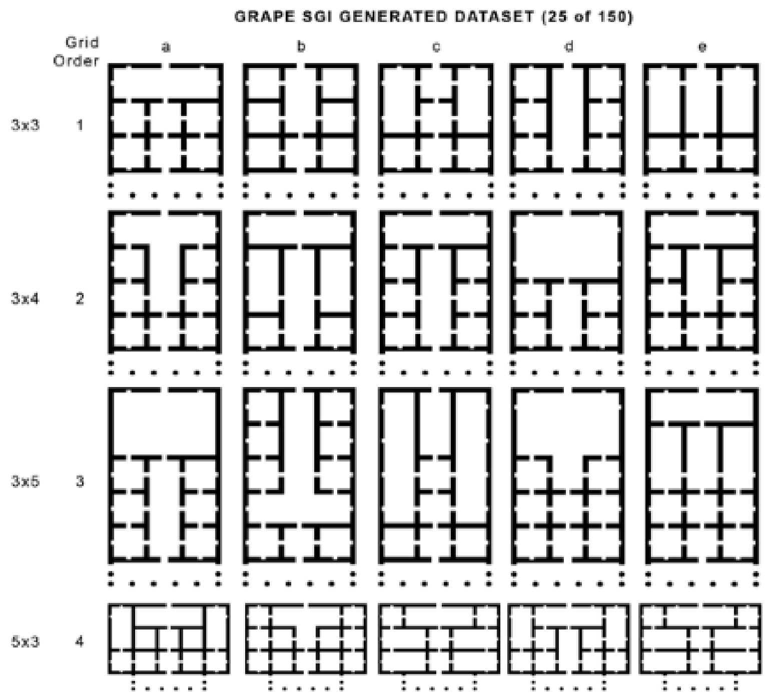

Figure 16: Generating Palladian villa plans by Uzun et al. (2020).

Floorplan Generation One of the first research areas of GANs in the built environment is the ability of GANs to generate spatially sensible floorplans. Using a GAN equipped with deep convolution layers (DCGAN), users can generate different layouts by adjusting the latent vector (Newton, 2019a,b). However, the generated results suffer from distortion and could not be used directly in the design process. Uzun et al. (2020) made a breakthrough in showing that DCGANs are capable of learning and reproducing floorplans in the style of Andrea Palladio after 6000 epochs of training (see Figure 16). Compared to the original floorplans, the reproduced floorplans are statistically and visually similar, although the spatial layouts are not satisfactory. (e.g., wrong organization of rooms and undesirable room sizes).

To improve the spatial layouts within the generated floorplans, researchers experimented with conditional GANs as it would support the encoding of individual spaces. In this way, users will be able to define parameters such as the size of the unit and the position of the rooms and walls in the generated floorplans (Zheng et al., 2020; Huang and Zheng, 2018). Rather than creating design options, this method simplifies the drawing process as designers simply need to draw colored boxes to generate production-ready floorplans that are colored and furnished with the correct elements. Research in this direction is mainly driven by datasets such as SCUT-AutoALP (Liu et al., 2020), which contains a large repository of colored floorplans with semantic masks and vector information, highlighting the importance of high-quality datasets for GAN performance.

The generative power of GANs is also used for floorplan optimization. Instead of generating floorplans from scratch or colored floorplans for presentation, Zhao et al. (2021b) used pix2pix to generate simplified spatial layouts of hospital floorplans. Using a bounding box as input, the model is able to generate good quality color-coded masks associated with different spatial functions in a hospital which has real engineering applications. However, the layouts are similar to human design, as it is limited by the provided training data, which is created by human designers.

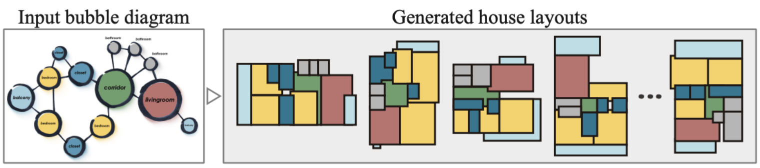

Figure 17: HouseGAN, a graph-based floorplan generator by Nauata et al. (2020).

Spatial Layout Generation Thus far, all floorplan generation tasks are intrinsically treated as image generation tasks. While the generated floorplans are visually compelling, none of the methods described above offer spatially compelling results (that is, a sensible spatial hierarchy between living rooms and bedrooms). This limitation is due to the inability of image generators to learn the spatial relations encoded in the input images. To overcome this, graph data and graph neural networks are introduced to encode and represent the spatial relationships between rooms. In a graph, floorplans are no longer represented by pixels, but by a collection of nodes and edges. As et al. (2018) and Eisenstadt et al. (2019) first demonstrated that GANs can be used to generate building topology graphs to quickly iterate through different spatial layouts based on different user requirements. Using a dataset of graphical floorplans represented in graphs, House-GAN (Nauata et al., 2020, 2021) improved on previous research to generate graphical floorplans from graph inputs. Multiple floorplan representations can be generated from the same topology while adapting to different boundary and size conditions. Furthermore, floorplans can be converted to vector data to create 3D models. This research offers a full innovative workflow in which AIs can suggest floorplan designs based on user requirements, and architects could improve the generated plans directly in a compatible CAD format (see Figure 17).

Since graph data are not limited by pixel resolution, layout generation at the city level is also now possible. Wang et al. (2020) embedded the spatial characteristics (e.g. value-added space, poi distribution, traffic condition) of different residential areas in a graph, and a GAN is used to learn the difference between well-planned and poorly planned areas. Owaki and Machida (2020) encoded road network information collected from OpenStreetMap in a spatial graph and trained a model to generate secondary and tertiary road networks given the contextual information.

Photo-realistic Rendering Artistic renderings of 3D models are currently generated through ray-tracing renders. Due to the fast inference speed of GANs, some researchers have speculated that GANs could speed up the rendering process, saving computational costs in the long run. Hong et al. (2020) and Gui et al. (2021b) used GANs to render different lighting conditions to speed up design iterations and Yang et al. (2019) are able to translate raw 3D geometries into interior scenes with rendering effect without actual ray-tracing computation. The custom framework is capable of producing more realistic and aesthetically pleasing renderings at both the detail and semantic levels compared to pix2pix. However, more research is needed to create production-ready renderings.

6. Discussion

6.1. General Observations

GANs are powerful deep learning models that can generate realistic representations of any form of data. All of these data formats can find their respective utility in the built environment at different scales. For example, satellite and GPS data for urban analytics, street view images for spatial quality transfer at the district level, graphs for spatial layouts at the building level.

From our review, it is evident that many innovative applications have been proposed, ranging from data augmentation, data synthesis, to design automation as mentioned in Section 5.3. Some of the applications in the review are alternatives to current workflows. For example, 3D urban reconstruction using GANs can be achieved through traditional procedural modeling (Kelly et al., 2017). Image feature extraction or semantic segmentation can also be achieved using other deep learning techniques (Minaee et al., 2020).

However, most applications covered by the corpus are GAN-only, offering unprecedented breakthroughs in AI in the built industry in tasks such as spatial layout generation, cross-view translation, and building facade restoration. Some applications in the review have already been implemented by commercial companies (He, 2020). We hope to see more of these technologies applied to the industry in the future.

As shown by the three thematic clusters in Section 5.3, GANs can be used independently or as part of a methodology. When used standalone, the experiments generally focus on design automation and data synthesis. When used as part of a methodology, GANs are used to upsample, up-res, or fill in missing data to optimize the performance of downstream processes.

The availability of open-source GAN repositories has greatly sped up research on the applications of GANs in various fields. Of the many GAN variants, image-to-image translation GANs are most popular in the built environment. This group of GANs, represented by pix2pix and CycleGAN, is highly versatile and offers state-of-the-art results for many applications. One of the most innovative uses is cross-view image translation, where aerial or satellite images can be converted into street view images with high fidelity and semantic accuracy (Deng et al., 2018; Regmi and Borji, 2018, 2019; Tang et al., 2019; Ding et al., 2020; Tang et al., 2020a). Another useful application is to generate functional architectural drawings, such as MEP pipe layouts or shear wall layouts that rival professionally created content (Liao et al., 2021; Sato et al., 2020).

GANs that process non-image data, such as graph, GPS, mobility, and building performance data, have also been extensively experimented in the corpus.

However, versatile repositories with plug-and-play features such as pix2pix are currently lacking, and high-quality datasets in this domain are generally closed to public access, raising the technical barrier of entry. As such, breakthroughs in this field, such as House-GAN and TrafficGAN, are mostly led by computer scientists or engineers rather than planners or designers.

6.2. Common Limitations

Data availability

Access to standardized and high-quality datasets is crucial to the development of GANs. As explained in Section 5.2, most openly accessible datasets are maintained by initiatives outside the built environment. Datasets that are specifically created for problems in the industry are much more limited.

For certain data types, such as satellite images and GPS data, the dataset used for training is large enough to harness the full power of GANs. On the other hand, many applications are carried out with much smaller datasets. This is especially prominent at the building scale as it is difficult to obtain a large set of high-quality dataset, and most research at this level resorted to collecting data individually. As a result, papers with low quality datasets have only scratched the surface of what GANs could help in the respective tasks, and the generated results are expected to be better as the quality of dataset improves.

An example of the impact of data quality can be seen from the solutions to floorplan layout generation. In earlier papers (Newton, 2019b,a; Huang and Zheng, 2018), the generated floorplans were largely unsatisfactory as the dataset was limited to a size of 100 images. In a later paper, Uzun et al. (2020) used a dataset of 2,525 floor plans with a uniform image style across samples to generate more realistic results. However, the model was still unable to learn the spatial correlations between different rooms in a floorplan as this information is not explicitly encoded in images. To overcome this limitation, HouseGAN converted a large dataset of 117,000 floorplans images into graph representations before training and obtained groundbreaking results in floorplan generation (Nauata et al., 2020). While the results of HouseGAN were already state-of-the-art, the authors were able to improve the results again by using a higher quality dataset in their next paper (Nauata et al., 2021). Compared to the original raster image dataset, the vector dataset is larger and does not require additional conversion, which eliminates the propagation of errors to downstream processes. The higher variety in the new dataset also expanded the model's ability to generalize to new conditions.

Computation Cost Another limitation of GANs is the high computational cost of running GAN models. Since GANs are equipped with two deep neural networks (generator and discriminator), the computational cost of GANs is even higher than that of many other deep learning methods. Training a StyleGAN at 1024x1024 resolution to match the photorealistic result shown in the original implementation requires 41 days and 4 hours using 1 Tesla V100 GPU and 6 days 14 hours using a 8 GPU cluster (Isola et al., 2017). Therefore, researchers must understand the cost of GANs and use them to perform tasks in which GANs excel. For example, although GANs can be used in semantic segmentation and sometimes achieve slightly better results, the computational resource needed to train the model is too great to justify large-scale deployment of such models for the task of semantic segmentation.

6.3. Research Opportunities

Large, high quality datasets As mentioned in the previous section, data availability is the common limitation for all GAN applications. In papers offering refreshing takes on the application of GANs, the authors often had to collect a large dataset before applying the model. Currently, only a handful of curated datasets are published for public use, and the landscape of open datasets in the built environment is still barren. To push the existing application of GANs to new heights, high-quality datasets can be published to improve the performance of models and serve as benchmarks for subsequent papers.

3DGANs A few papers in 3D reconstruction gave us a sneak peek into the untapped potential of 3DGANs. However, the existing methods covered in the corpus did not use 3D models in the training of GANs. Instead, multiple 2D images are stitched together to form 3D models. With more 3D data available in the future (e.g. 3D models and point clouds), GANs can be applied on 3D data formats directly using generators that support these datasets. Currently, GANs that could generate 3D models have already been created, and their potential application to the built environment remains untapped.

GraphGANs Graph data is an excellent data format that contains spatial relationships, which is a crucial property in the built environment (Liu and Biljecki, 2022). The contextual information carried by graphs has already made a breakthrough in floorplan generation. Many more properties in the built environment can be represented in graphs, for example, urban road networks, neighborhood masterplans, and building occupancy. As fundamental research on graph representational learning and graph GANs continues to involve, future research of their application in the industry would bring AIs with much greater spatial intelligence across all scales.

Human-GAN Interaction Although GANs require high computational cost during training, their inference can be instantaneous. In the corpus, we have seen how GANs can be used by architects as a tool for design inspiration. Also, in the field of human-computer interaction, designers have experimented with using GANs to visualize real-time changes in urban streetscapes based on design decisions made with an augmented reality setup (Noyman and Larson, 2020). These papers free our imagination of the capabilities of GANs when combined with more intuitive operational logic and a future where architects and planners would use GANs as copilots in design projects.

7. Conclusion

Combining the power of GANs with the growing wealth of data available in the built environment, groundbreaking AIs can be created to help humans in urban understanding and to create innovative solutions to problems in the industry. Through examining 100 recently published papers, we have shown that GANs are now being used in 26 different applications at the city, district, and building scale. Some studies in the corpus have used GANs to solve problems that were unsolvable using traditional methods, and others have used GANs to optimize current workflows. The primary limitation that holds back research in GANs in the industry is the lack of high-quality datasets that are specifically designed to address problems in the built environment. Furthermore, studies that have set the state-of-the-art in their respective tasks also require more user-friendly interfaces to bring these applications into mainstream workflows to benefit planners, analysts, and designers.

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References

Abdollahi, A., Pradhan, B., Gite, S., Alamri, A., 2020. Building Footprint Extraction from High Resolution Aerial Images Using Generative Adversarial Network (GAN) Architecture. IEEE Access 8, 209517–209527. doi:10.1109/ACCESS.2020.3038225.

Aggarwal, A., Mittal, M., Battineni, G., 2021. Generative adversarial network: An overview of theory and applications. International Journal of Information Management Data Insights 1, 100004.

Alawadhi, M., Yan, W., 2021. Bim hyperreality: Data synthesis using bim and hyperrealistic rendering for deep learning. arXiv:2105.04103 [cs] URL: http://arxiv.org/abs/2105.04103. arXiv: 2105.04103.

Albert, A., Strano, E., Kaur, J., Gonzalez, M., 2018. Modeling urbanization patterns with generative adversarial networks.

Arjovsky, M., Chintala, S., Bottou, L., 2017. Wasserstein generative adversarial networks, in: Precup, D., Teh, Y.W. (Eds.), Proceedings of the 34th International Conference on Machine Learning, PMLR. pp. 214–223. URL: https://proceedings.mlr.press/v70/arjovsky17a.html.

As, I., Pal, S., Basu, P., 2018. Artificial intelligence in architecture: Generating conceptual design via deep learning. International Journal of Architectural Computing 16, 306–327. doi:10.1177/1478077118800982.

Beaulieu-Jones, B.K., Wu, Z.S., Williams, C., Lee, R., Bhavnani, S.P., Byrd, J.B., Greene, C.S., 2019. Privacy-preserving generative deep neural networks support clinical data sharing. Circulation: Cardiovascular Quality and Outcomes 12, e005122.

Biljecki, F., Ito, K., 2021. Street view imagery in urban analytics and GIS: A review. Landscape and Urban Planning 215, 104217. doi:10.1016/j.landurbplan.2021.104217.

Bittner, K., Koerner, M., Reinartz, P., 2019. Dsm building shape refinement from combined remote sensing images based on wnet-cgans.

Bittner, K., Korner, M., 2018. Automatic large-scale 3d building shape refinement using conditional generative adversarial networks, in: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, IEEE Computer Society. pp. 1968–1970. doi:10.1109/CVPRW.2018.00249.

Bowles, C., Gunn, R., Hammers, A., Rueckert, D., 2018. Gansfer learning: Combining labelled and unlabelled data for gan based data augmentation. arXiv preprint arXiv:1811.10669 .

Brock, A., Donahue, J., Simonyan, K., 2018. Large scale gan training for high fidelity natural image synthesis. arXiv preprint arXiv:1809.11096 .

Campo, M., 2021. Architecture, language and ai: Language, attentional generative adversarial networks (attngan) and architecture design, in: Projections - Proceedings of the 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia, CAADRIA 2021, pp. 211–220.

Chan, Y.H.E., Spaeth, A.B., 2020. Architectural Visualisation with Conditional Generative Adversarial Networks (cGAN), in: Proceedings of the 38th eCAADe Conference, pp. 299–308.

Chaturvedi, V., de Vries, W.T., 2021. Machine Learning Algorithms for Urban Land Use Planning: A Review. Urban Science 5, 68. URL: https://www.mdpi.com/2413-8851/5/3/68, doi:10.3390/urbansci5030068. number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

Chen, J., Stouffs, 2021. From exploration to interpretation - adopting deep representation learning models to latent space interpretation of architectural design alternatives, in: A. Globa, J. van Ameijde, A. Fingrut, N. Kim, T.T.S. Lo (eds.), PROJECTIONS - Proceedings of the 26th CAADRIA Conference - Volume 1, The Chinese University of Hong Kong and Online, Hong Kong, 29 March - 1 April 2021, pp. 131-140, CUMINCAD. URL: http://papers.cumincad.org/cgi-bin/works/paper/caadria2021_038.

Chen, Y., Ouyang, X., Agam, G., 2019. Changenet: Learning to detect changes in satellite images, in: Proceedings of the 3rd ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery, GeoAI 2019, Association for Computing Machinery, Inc.

pp. 24–31. doi:10.1145/3356471.3365232.
Cho, D., Kim, J., Shin, E., Choi, J., Lee, J.K., 2020. Recognizing architectural objects in floor-plan drawings using deep-learning style-transfer algorithms , 9.
Chokwitthaya, C., Collier, E., Zhu, Y., Mukhopadhyay, S., 2019. Improving prediction accuracy in building performance models using generative adversarial networks (gans), in: Proceedings of the International Joint Conference on Neural Networks, Institute of Electrical and Electronics Engineers Inc. doi:10.1109/IJCNN.2019.8852411.
Chokwitthaya, C., Zhu, Y., Mukhopadhyay, S., Collier, E., 2020. Augmenting building performance predictions during design using generative adversarial networks and immersive virtual environments. Automation in Construction 119. doi:10.1016/j.autcon.2020.103350.
Creswell, A., White, T., Dumoulin, V., Arulkumaran, K., Sengupta, B., Bharath, A.A., 2018. Generative adversarial networks: An overview. IEEE Signal Processing Magazine 35, 53–65. doi:10.1109/MSP.2017.2765202.
Danchenko, E., 2021. The AI-teration Method and the Role of AI in Architectural Design. Advances in Intelligent Systems and Computing 1288, 525–538. doi:10.1007/978-3-030-63128-4_40.
Deng, X., Zhu, Y., Newsam, S., 2018. What Is It Like Down There? Generating Dense Ground-Level Views and Image Features From Overhead Imagery Using Conditional Generative Adversarial Networks. doi:10.1145/3274895.3274969.
Ding, H., Wu, S., Tang, H., Wu, F., Gao, G., Jing, X.Y., 2020. Cross-view image synthesis with deformable convolution and attention mechanism. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 12305 LNCS, 386–397. doi:10.1007/978-3-030-60633-6_32.
Dong, H.W., Hsiao, W.Y., Yang, L.C., Yang, Y.H., 2018. Musegan: Multi-track sequential generative adversarial networks for symbolic music generation and accompaniment, in: Proceedings of the AAAI Conference on Artificial Intelligence.
Dong, S., Wang, W., Li, W., Zou, K., 2021. Vectorization of floor plans based on EdgeGAN. Information (Switzerland) 12. doi:10.3390/info12050206.
Du, Z., Shen, H., Li, X., Wang, M., 2020. 3d building fabrication with geometry and texture coordination via hybrid gan. Journal of Ambient Intelligence and Humanized Computing doi:10.1007/s12652-020-02488-9.
Eisenstadt, V., Langenhan, C., Althoff, K.D., 2019. Generation of floor plan variations with convolutional neural networks and case-based reasoning an approach for transformative adaptation of room configurations within a framework for support of early conceptual design phases.
Gao, N., Xue, H., Shao, W., Zhao, S., Qin, K.K., Prabowo, A., Rahaman, M.S., Salim, F.D., 2022. Generative Adversarial Networks for Spatio-temporal Data: A Survey. ACM Transactions on Intelligent Systems and Technology 13, 1–25. doi:10.1145/3474838.
Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative adversarial nets. Advances in neural information processing systems 27.
Gui, J., Sun, Z., Wen, Y., Tao, D., Ye, J., 2021a. A review on generative adversarial networks: Algorithms, theory, and applications. IEEE Transactions on Knowledge and Data Engineering .
Gui, Y., Zhou, B., Xie, X., Li, W., Zhou, X., 2021b. GAN-based method for generative design of visual comfort in underground space, in: IOP Conference Series: Earth and Environmental Science, IOP Publishing Ltd. doi:10.1088/1755-1315/861/7/072015.

He, Q., Li, Z., Gao, W., Chen, H., Wu, X., Cheng, X., Lin, B., 2021. Predictive models for daylight performance of general floorplans based on cnn and gan: A proof-of-concept study. Building and Environment 206. doi:10.1016/j.buildenv.2021.108346.

He, W., 2020. Urban experiment: Taking off on the wind of al. Architectural Design 90, 94–99. doi:10.1002/ad.2574.

Hettiarachchi, P., Nawaratne, R., Alahakoon, D., De Silva, D., Chilamkurti, N., 2021. Rain streak removal for single images using conditional generative adversarial networks. doi:10.3390/app11052214.

Hong, Y., Park, S., Kim, H., 2020. Synthetic data generation for indoor scene understanding using bim, in: Proceedings of the 37th International Symposium on Automation and Robotics in Construction, ISARC 2020: From Demonstration to Practical Use - To New Stage of Construction Robot, International Association on Automation and Robotics in Construction (IAARC). pp. 334–338.

Hou, B., Liu, Q., Wang, H., Wang, Y., 2020. From W-Net to CDGAN: Bitemporal Change Detection via Deep Learning Techniques. IEEE Transactions on Geoscience and Remote Sensing 58, 1790–1802. doi:10.1109/TGRS.2019.2948659.

Huang, J., Johanes, M., Kim, F., Doumpioti, C., Holz, G.C., 2021. On gans, nlp and architecture: Combining human and machine intelligences for the generation and evaluation of meaningful designs. Technology Architecture and Design 5, 207–224. doi:10.1080/24751448.2021.1967060.

Huang, W., Zheng, H., 2018. Architectural drawings recognition and generation through machine learning, in: Recalibration on Imprecision and Infidelity - Proceedings of the 38th Annual Conference of the Association for Computer Aided Design in Architecture, ACADIA 2018, ACADIA. pp. 156–165.

Hughes, R.T., Zhu, L., Bednarz, T., 2021. Generative Adversarial Networks–Enabled Human–Artificial Intelligence Collaborative Applications for Creative and Design Industries: A Systematic Review of Current Approaches and Trends. Frontiers in Artificial Intelligence 4. URL: https://www.frontiersin.org/article/10.3389/frai.2021.604234.

Ibrahim, H., Khattab, Z., Khattab, T., Abraham, R., . Expatriates' housing dispersal outlook in a rapidly developing metropolis based on urban growth predicted using a machine learning algorithm. doi:10.1080/10511482.2021.1962939.

Ikeno, K., Fukuda, T., Yabuki, N., 2021. An enhanced 3d model and generative adversarial network for automated generation of horizontal building mask images and cloudless aerial photographs. Advanced Engineering Informatics 50. doi:10.1016/j.aei.2021.101380.

Isola, P., Zhu, J.Y., Zhou, T., Efros, A.A., 2017. Image-to-image translation with conditional adversarial networks, in: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1125–1134.

Johnsen, M., Brandt, O., Garrido, S., Pereira, F., 2021. Population synthesis for urban resident modeling using deep generative models. Neural Computing and Applications doi:10.1007/s00521-021-06622-2.

Kang, Y., Gao, S., Roth, R., 2019. Transferring multiscale map styles using generative adversarial networks. International Journal of Cartography 5, 115–141. doi:10.1080/23729333.2019.1615729.

Karras, T., Aittala, M., Laine, S., Härkönen, E., Hellsten, J., Lehtinen, J., Aila, T., 2021. Alias-free generative adversarial networks, in: Ranzato, M., Beygelzimer, A., Dauphin, Y., Liang, P.S., Vaughan, J.W. (Eds.), Advances in Neural Information Processing Systems, Curran

Associates, Inc.. pp. 852–863. URL: https://proceedings.neurips.cc/paper/2021/file/076ccd93ad68be51f23707988e934906-Paper.pdf.
Karras, T., Laine, S., Aila, T., 2019. A style-based generator architecture for generative adversarial networks URL: http://arxiv.org/abs/1812.04948, arXiv:1812.04948.
Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., Aila, T., 2020. Analyzing and improving the image quality of StyleGAN URL: http://arxiv.org/abs/1912.04958, arXiv:1912.04958.
Kelly, T., Femiani, J., Wonka, P., Mitra, N.J., 2017. BigSUR: large-scale structured urban reconstruction. ACM Transactions on Graphics 36, 204:1–204:16. doi:10.1145/3130800.3130823.
Kelly, T., Guerrero, P., Steed, A., Wonka, P., Mitra, N.J., 2018. Frankengan: guided detail synthesis for building mass models using style-synchonized gans. ACM Transactions on Graphics 37, 1–14. doi:10.1145/3272127.3275065.
Kim, S., Kim, D., Choi, S., 2020. Citycraft: 3d virtual city creation from a single image. Visual Computer 36, 911–924. doi:10.1007/s00371-019-01701-x.
Kim, S., Park, S., Kim, H., Yu, K., 2021. Deep floor plan analysis for complicated drawings based on style transfer. Journal of Computing in Civil Engineering 35. doi:10.1061/(ASCE)CP.1943-5487.0000942.
Kim, S., Park, S., Yu, K., 2018. Application of style transfer in the vectorization process of floorplans (short paper) , 6 pagesdoi:10.4230/LIPICS.GISCIENCE.2018.39.
Lee, Y.O., Jo, J., Hwang, J., 2017. Application of deep neural network and generative adversarial network to industrial maintenance: A case study of induction motor fault detection, in: 2017 IEEE international conference on big data (big data), IEEE. pp. 3248–3253.
Li, J., Chen, Z., Zhao, X., Shao, L., 2020. Mapgan: An intelligent generation model for network tile maps. Sensors (Basel, Switzerland) 20, 3119. doi:10.3390/s20113119.
Li, J., He, F., Zhang, L., Du, B., Tao, D., 2019. Progressive reconstruction of visual structure for image inpainting, in: Proceedings of the IEEE International Conference on Computer Vision, Institute of Electrical and Electronics Engineers Inc.. pp. 5961–5970. doi:10.1109/ICCV.2019.00606.
Li, Y., Liu, S., Yang, J., Yang, M.H., 2017. Generative face completion, in: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 3911–3919.
Liao, W., Lu, X., Huang, Y., Zheng, Z., Lin, Y., 2021. Automated structural design of shear wall residential buildings using generative adversarial networks. Automation in Construction 132. doi:10.1016/j.autcon.2021.103931.
Litjens, G., Ciompi, F., Wolterink, J.M., de Vos, B.D., Leiner, T., Teuwen, J., Išgum, I., 2019. State-of-the-art deep learning in cardiovascular image analysis. JACC: Cardiovascular Imaging 12, 1549–1565. URL: https://doi.org/10.1016%2Fj.jcmg.2019.06.009, doi:10.1016/j.jcmg.2019.06.009.
Liu, H., Wan, Z., Huang, W., Song, Y., Han, X., Liao, J., 2021. Pd-gan: Probabilistic diverse gan for image inpainting. doi:10.1109/CVPR46437.2021.00925.
Liu, P., Biljecki, F., 2022. A Review of Spatially-explicit GeoAI Applications in Urban Geography. International Journal of Applied Earth Observation and Geoinformation 112, 102936. doi:10.1016/j.jag.2022.102936.
Liu, Y., Lai, Y., Chen, J., Liang, L., Deng, Q., 2020. Scut-autoalp: A diverse benchmark dataset for automatic architectural layout parsing. IEICE Transactions on Information and Systems E103D, 2725–2729. doi:10.1587/transinf.2020EDL8076.

Minaee, S., Boykov, Y., Porikli, F., Plaza, A., Kehtarnavaz, N., Terzopoulos, D., 2020. Image segmentation using deep learning: A survey. arXiv:2001.05566 [cs] URL: http://arxiv.org/abs/2001.05566.

Nauata, N., Chang, K.H., Cheng, C.Y., Mori, G., Furukawa, Y., 2020. House-gan: Relational generative adversarial networks for graph-constrained house layout generation. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 12346 LNCS, 162–177. doi:10.1007/978-3-030-58452-8_10.

Nauata, N., Hosseini, S., Chang, K.H., Chu, H., Cheng, C.Y., Furukawa, Y., 2021. House-gan++: Generative adversarial layout refinement network towards intelligent computational agent for professional architects, in: 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), IEEE. pp. 13627–13636. URL: https://ieeexplore.ieee.org/document/9577959/, doi:10.1109/CVPR46437.2021.01342.

Navarro-Mateu, D., Carrasco, O., Nieves, P., 2021. Color-patterns to architecture conversion through conditional generative adversarial networks. Biomimetics 6, 1–20. doi:10.3390/biomimetics6010016.

Newton, D., 2019a. Deep generative learning for the generation and analysis of architectural plans with small datasets.

Newton, D., 2019b. Generative deep learning in architectural design. Technology Architecture and Design 3, 176–189. doi:10.1080/24751448.2019.1640536.

Noyman, A., Larson, K., 2020. A deep image of the city: generative urban-design visualization, in: Proceedings of the 11th Annual Symposium on Simulation for Architecture and Urban Design, Society for Computer Simulation International. pp. 1–8.

Ntavelis, E., Romero, A., Kastanis, I., Van Gool, L., Timofte, R., 2020. SESAME: Semantic editing of scenes by adding, manipulating or erasing objects, in: Vedaldi, A., Bischof, H., Brox, T., Frahm, J.M. (Eds.), Computer Vision – ECCV 2020. Springer International Publishing. volume 12367, pp. 394–411. URL: https://link.springer.com/10.1007/978-3-030-58542-6_24, doi:10.1007/978-3-030-58542-6_24. series Title: Lecture Notes in Computer Science.

Owaki, T., Machida, T., 2020. RoadNetGAN: Generating Road Networks in Planar Graph Representation. Springer International Publishing. volume 1332 of *Communications in Computer and Information Science*. pp. 535–543. URL: https://link.springer.com/10.1007/978-3-030-63820-7_61, doi:10.1007/978-3-030-63820-7_61.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P., Moher, D., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews 372. URL: https://www.bmj.com/content/372/bmj.n71, doi:10.1136/bmj.n71. publisher: BMJ Publishing Group Ltd _eprint: https://www.bmj.com/content/372/bmj.n71.full.pdf.

Pang, H.E., Biljecki, F., 2022. 3D building reconstruction from single street view images using deep learning. International Journal of Applied Earth Observation and Geoinformation 112, 102859. doi:10.1016/j.jag.2022.102859.

Park, T., Liu, M.Y., Wang, T.C., Zhu, J.Y., 2019. Semantic image synthesis with spatially-adaptive normalization, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 2337–2346.

Pascual, S., Bonafonte, A., Serra, J., 2017. Segan: Speech enhancement generative adversarial network. arXiv preprint arXiv:1703.09452 .

Pasquero, C., Poletto, M., 2020. Deepgreen - coupling biological and artificial intelligence in urban design, in: Proceedings of the 40th Annual Conference of the Association for Computer Aided Design in Architecture: Distributed Proximities, ACADIA 2020, ACADIA. pp. 668–677.

Pathak, D., Krahenbuhl, P., Donahue, J., Darrell, T., Efros, A.A., 2016. Context encoders: Feature learning by inpainting, in: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2536–2544.

Pham, V.D., Bui, Q.T., 2021. Spatial resolution enhancement method for landsat imagery using a generative adversarial network. doi:10.1080/2150704X.2021.1918789.

Qian, W., Xu, Y., Li, H., 2021. A self-sparse generative adversarial network for autonomous early-stage design of architectural sketches. Computer-Aided Civil and Infrastructure Engineering doi:10.1111/mice.12759.

Qin, X., Chen, W., Shen, Q., Jiang, J., Feng, G., 2018. Image inpainting: A contextual consistent and deep generative adversarial training approach, in: Proceedings - 4th Asian Conference on Pattern Recognition, ACPR 2017, Institute of Electrical and Electronics Engineers Inc.. pp. 594–598. doi:10.1109/ACPR.2017.120.

Quintana, M., Schiavon, S., Tham, K.W., Miller, C., 2020. Balancing thermal comfort datasets. Proceedings of the 7th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation , 120–129doi:10.1145/3408308.3427612, arXiv:2009.13154.

Rachele, J.N., Wang, J., Wijnands, J.S., Zhao, H., Bentley, R., Stevenson, M., 2021. Using machine learning to examine associations between the built environment and physical function: A feasibility study. Health & Place 70, 102601. doi:10.1016/j.healthplace.2021.102601.

Radford, A., Metz, L., Chintala, S., 2015. Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434 .

Regmi, K., Borji, A., 2018. Cross-view image synthesis using conditional gans, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, IEEE Computer Society. pp. 3501–3510. doi:10.1109/CVPR.2018.00369.

Regmi, K., Borji, A., 2019. Cross-view image synthesis using geometry-guided conditional gans. Computer Vision and Image Understanding 187. doi:10.1016/j.cviu.2019.07.008.

Roth, K., Lucchi, A., Nowozin, S., Hofmann, T., 2017. Stabilizing training of generative adversarial networks through regularization, in: Advances in Neural Information Processing Systems, Curran Associates, Inc. URL: https://proceedings.neurips.cc/paper/2017/hash/7bccfde7714a1ebadf06c5f4cea752c1-Abstract.html.

Salimans, T., Zhang, H., Radford, A., Metaxas, D., 2018. Improving GANs using optimal transport, in: International Conference on Learning Representations. URL: https://openreview.net/forum?id=rkQkBnJAb.

Sato, G., Ishizawa, T., Iseda, H., Kitahara, H., 2020. Automatic generation of the schematic mechanical system drawing by generative adversarial network , 8.

Sharma, D., Gupta, N., Chattopadhyay, C., Mehta, S., 2019. Rexplore: A sketch based interactive explorer for real estates using building floor plan images, in: Proceedings - 2018 IEEE International Symposium on Multimedia, ISM 2018, Institute of Electrical and Electronics Engineers Inc.. pp. 61–64. doi:10.1109/ISM.2018.00018.

Shen, J., Liu, C., Ren, Y., Zheng, H., 2020. Machine learning assisted urban filling, in: RE: Anthropocene, Design in the Age of Humans - Proceedings of the 25th International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA 2020, The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA). pp. 681–690.

Shi, Q., Liu, X., Li, X., 2017. Road detection from remote sensing images by generative adversarial networks. IEEE Access 6, 25486–25494. doi:10.1109/ACCESS.2017.2773142.

Steinfeld, K., 2019. Gan loci imaging place using generative adversarial networks, in: Ubiquity and Autonomy - Paper Proceedings of the 39th Annual Conference of the Association for Computer Aided Design in Architecture, ACADIA 2019, ACADIA. pp. 392–403.

Sun, C., Zhou, Y., Han, Y., 2022. Automatic generation of architecture facade for historical urban renovation using generative adversarial network. Building and Environment 212. doi:10.1016/j.buildenv.2022.108781.

Sun, S., Mu, L., Feng, R., Wang, L., He, J., 2021a. Gan-based lucc prediction via the combination of prior city planning information and land-use probability. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 14, 10189–10198. doi:10.1109/JSTARS.2021.3106481.

Sun, S., Mu, L., Wang, L., Liu, P., Liu, X., Zhang, Y., 2021b. Semantic segmentation for buildings of large intra-class variation in remote sensing images with o-gan. Remote Sensing 13, 1–21. doi:10.3390/rs13030475.

Tang, H., Liu, H., Sebe, N., 2020a. Unified generative adversarial networks for controllable image-to-image translation. IEEE Transactions on Image Processing 29, 8916–8929. doi:10.1109/TIP.2020.3021789.

Tang, H., Xu, D., Sebe, N., Wang, Y., Corso, J.J., Yan, Y., 2019. Multi-channel attention selection gan with cascaded semantic guidance for cross-view image translation. arXiv:1904.06807 [cs] URL: http://arxiv.org/abs/1904.06807. arXiv: 1904.06807.

Tang, H., Xu, D., Yan, Y., Torr, P., Sebe, N., 2020b. Local class-specific and global image-level generative adversarial networks for semantic-guided scene generation, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, IEEE Computer Society. pp. 7867–7876.

Toker, A., Zhou, Q., Maximov, M., Leal-Taixé, L., 2021. Coming down to earth: Satellite-to-street view synthesis for geo-localization. arXiv:2103.06818.

Uzun, C., Çolakoğlu, M., İnceoğlu, A., 2020. Gan as a generative architectural plan layout tool: A case study for training dcgan with palladian plans and evaluation of dcgan outputs. A/Z ITU Journal of the Faculty of Architecture 17, 185–198. doi:10.5505/itujfa.2020.54037.

Varia, N., Dokania, A., Senthilnath, J., 2019. Deepext: A convolution neural network for road extraction using rgb images captured by uav, in: Proceedings of the 2018 IEEE Symposium Series on Computational Intelligence, SSCI 2018, Institute of Electrical and Electronics Engineers Inc.. pp. 1890–1895. doi:10.1109/SSCI.2018.8628717.

Venator, M., Aklanoglu, S., Bruns, E., Maier, A., 2021. Enhancing collaborative road scene reconstruction with unsupervised domain alignment. Machine Vision and Applications 32. doi:10.1007/s00138-020-01144-8.

Wang, D., Fu, Y., Wang, P., Huang, B., Lu, C.T., 2020. Reimagining city configuration: Automated urban planning via adversarial learning, in: GIS: Proceedings of the ACM International Symposium on Advances in Geographic Information Systems, Association for Computing Machinery. pp. 497–506. doi:10.1145/3397536.3422268.

Wang, H., Wang, J., Wang, J., Zhao, M., Zhang, W., Zhang, F., Xie, X., Guo, M., 2017a. Graphgan: Graph representation learning with generative adversarial nets. arXiv:1711.08267 [cs, stat] URL: http://arxiv.org/abs/1711.08267. arXiv: 1711.08267.

Wang, H., Wang, J., Wang, J., Zhao, M., Zhang, W., Zhang, F., Xie, X., Guo, M., 2018a. Graphgan: Graph representation learning with generative adversarial nets, in: Proceedings of the AAAI conference on artificial intelligence.

Wang, K., Gou, C., Duan, Y., Lin, Y., Zheng, X., Wang, F.Y., 2017b. Generative adversarial networks: introduction and outlook. IEEE/CAA Journal of Automatica Sinica 4, 588–598.

Wang, M., Yang, G.Y., Li, R., Liang, R.Z., Zhang, S.H., Hall, P., Hu, S.M., 2019a. Example-guided style-consistent image synthesis from semantic labeling, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, IEEE Computer Society. pp. 1495–1504. doi:10.1109/CVPR.2019.00159.

Wang, N., Zeng, X., Xie, R., Gao, Z., Zheng, Y., Liao, Z., Yang, J., Wang, Q., 2019b. Unsupervised classification of street architectures based on infogan. arXiv:1905.12844 [cs] URL: http://arxiv.org/abs/1905.12844. arXiv: 1905.12844.

Wang, S., Cao, D., Lin, D., Chao, F., 2018b. Traffic Condition Analysis Based on Users Emotion Tendency of Microblog. Springer International Publishing. volume 650 of *Advances in Intelligent Systems and Computing*. pp. 299–311. URL: http://link.springer.com/10.1007/978-3-319-66939-7_26, doi:10.1007/978-3-319-66939-7_26.

Wang, S.M., Huang, C.J., 2019. Using space syntax and information visualization for spatial behavior analysis and simulation. International Journal of Advanced Computer Science and Applications 10, 510–521. doi:10.14569/ijacsa.2019.0100463.

Wang, T.C., Liu, M.Y., Zhu, J.Y., Tao, A., Kautz, J., Catanzaro, B., 2018c. High-resolution image synthesis and semantic manipulation with conditional GANs URL: http://arxiv.org/abs/1711.11585, arXiv:1711.11585.

Wang, Y., Zorzi, S., Bittner, K., 2021. Machine-learned 3d building vectorization from satellite imagery. doi:10.1109/CVPRW53098.2021.00118.

Wijnands, J., Nice, K., Thompson, J., Zhao, H., Stevenson, M., 2019. Streetscape augmentation using generative adversarial networks: Insights related to health and wellbeing. Sustainable Cities and Society 49. doi:10.1016/j.scs.2019.101602.

Wu, A.N., Biljecki, F., 2022. GANmapper: geographical data translation. International Journal of Geographical Information Science 36, 1394–1422. doi:10.1080/13658816.2022.2041643.

Wu, W., Qi, H., Rong, Z., Liu, L., Su, H., 2018. Scribble-supervised segmentation of aerial building footprints using adversarial learning. IEEE Access 6, 58898–58911. doi:10.1109/ACCESS.2018.2874544.

Xu, C., Zhao, B., 2018. Satellite image spoofing: Creating remote sensing dataset with generative adversarial networks (short paper) , 6 pagesdoi:10.4230/LIPICS.GISCIENCE.2018.67.

Xu, T., Zhang, P., Huang, Q., Zhang, H., Gan, Z., Huang, X., He, X., 2017. Attngan: Fine-grained text to image generation with attentional generative adversarial networks. arXiv:1711.10485 [cs] URL: http://arxiv.org/abs/1711.10485. arXiv: 1711.10485.

Yan, K., Chong, A., Mo, Y., 2020. Generative adversarial network for fault detection diagnosis of chillers. Building and Environment 172, 106698. doi:10.1016/j.buildenv.2020.106698.

Yang, B., Kang, Y., Yuan, Y., Li, H., Wang, F., 2021. St-fvgan: filling series traffic missing values with generative adversarial network. Transportation Letters 0, 1–9. doi:10.1080/19427867.2021.1879624.

Yang, F., Lu, Z., Qiu, G., Lin, J., Zhang, Q., 2019. Capsule Based Image Synthesis for Interior Design Effect Rendering. Springer International Publishing. volume 11365 of *Lecture Notes in Computer Science*. pp. 183–198. URL: http://link.springer.com/10.1007/978-3-030-20873-8_12, doi:10.1007/978-3-030-20873-8_12.

Yao, J., Huang, C., Peng, X., Yuan, P., 2021. Generative design method of building group: Based on generative adversarial network and genetic algorithm, in: Projections - Proceedings of the 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia, CAADRIA 2021, The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA). pp. 61–70.

Ye, X., Du, J., Ye, Y., 2021. Masterplangan: Facilitating the smart rendering of urban master plans via generative adversarial networks. Environment and Planning B: Urban Analytics and City Science doi:10.1177/23998083211023516.

Yeh, R.A., Chen, C., Yian Lim, T., Schwing, A.G., Hasegawa-Johnson, M., Do, M.N., 2017. Semantic image inpainting with deep generative models, in: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 5485–5493.

Yu, D., 2020. Reprogramming urban block by machine creativity how to use neural networks as generative tools to design space.

Yu, J., Lin, Z., Yang, J., Shen, X., Lu, X., Huang, T.S., 2018. Generative image inpainting with contextual attention. arXiv preprint arXiv:1801.07892 .

Zakharov, E., Shysheya, A., Burkov, E., Lempitsky, V., 2019. Few-shot adversarial learning of realistic neural talking head models, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 9459–9468.

Zhang, G., Rui, X., Poslad, S., Song, X., Fan, Y., Wu, B., 2020a. A method for the estimation of finely-grained temporal spatial human population density distributions based on cell phone call detail records. Remote Sensing 12. doi:10.3390/RS12162572.

Zhang, H., Blasetti, E., 2020. 3d architectural form style transfer through machine learning, in: RE: Anthropocene, Design in the Age of Humans - Proceedings of the 25th International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA 2020, The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA). pp. 661–670.

Zhang, H., Hu, Z., Luo, C., Zuo, W., Wang, M., 2018. Semantic image inpainting with progressive generative networks, in: MM 2018 - Proceedings of the 2018 ACM Multimedia Conference, Association for Computing Machinery, Inc. pp. 1939–1947. doi:10.1145/3240508.3240625.

Zhang, J., Fukuda, T., Yabuki, N., 2021. Automatic object removal with obstructed facades completion using semantic segmentation and generative adversarial inpainting. IEEE Access doi:10.1109/ACCESS.2021.3106124.

Zhang, S., Han, Z., Lai, Y.K., Zwicker, M., Zhang, H., 2019a. Stylistic scene enhancement gan: mixed stylistic enhancement generation for 3d indoor scenes. Visual Computer 35, 1157–1169. doi:10.1007/s00371-019-01691-w.

Zhang, Y., Li, Y., Zhou, X., Kong, X., Luo, J., 2019b. Trafficgan: Off-deployment traffic estimation with traffic generative adversarial networks, in: Proceedings - IEEE International Conference on Data Mining, ICDM, Institute of Electrical and Electronics Engineers Inc.. pp. 1474–1479. doi:10.1109/ICDM.2019.00193.

Zhang, Y., Li, Y., Zhou, X., Kong, X., Luo, J., 2020b. Off-deployment traffic estimation — a traffic generative adversarial networks approach. IEEE Transactions on Big Data doi:10.1109/TBDATA.2020.3014511.

Zhang, Y., Yin, Y., Zimmermann, R., Wang, G., Varadarajan, J., Ng, S.K., 2020c. An enhanced gan model for automatic satellite-to-map image conversion. IEEE Access 8, 176704–176716. doi:10.1109/ACCESS.2020.3025008.

Zhao, B., Zhang, S., Xu, C., Sun, Y., Deng, C., 2021a. Deep fake geography? when geospatial data encounter artificial intelligence. Cartography and Geographic Information Science 48, 338–352. doi:10.1080/15230406.2021.1910075.

Zhao, C., Yang, J., Xiong, W., Li, J., 2021b. Two generative design methods of hospital operating department layouts based on healthcare systematic layout planning and generative adversarial network. Journal of Shanghai Jiaotong University (Science) 26, 103–115. doi:10.1007/s12204-021-2265-9.

Zhao, H., Wijnands, J.S., Nice, K.A., Thompson, J., Aschwanden, G.D.P.A., Stevenson, M., Guo, J., 2019. Unsupervised Deep Learning to Explore Streetscape Factors Associated with Urban Cyclist Safety. Springer Singapore. volume 149 of *Smart Innovation, Systems and Technologies*. pp. 155–164. URL: http://link.springer.com/10.1007/978-981-13-8683-1_16, doi:10.1007/978-981-13-8683-1_16.

Zhao, L., Mo, Q., Lin, S., Wang, Z., Zuo, Z., Chen, H., Xing, W., Lu, D., 2020. Uctgan: Diverse image inpainting based on unsupervised cross-space translation, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, IEEE Computer Society. pp. 5740–5749. doi:10.1109/CVPR42600.2020.00578.

Zheng, H., An, K., Wei, J., Ren, Y., 2020. Apartment floor plans generation via generative adversarial networks, in: RE: Anthropocene, Design in the Age of Humans - Proceedings of the 25th International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA 2020, The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA). pp. 601–610.

Zhu, D., Cheng, X., Zhang, F., Yao, X., Gao, Y., Liu, Y., 2020a. Spatial interpolation using conditional generative adversarial neural networks. International Journal of Geographical Information Science 34, 735–758. doi:10.1080/13658816.2019.1599122.

Zhu, J.Y., Park, T., Isola, P., Efros, A.A., 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks, in: Proceedings of the IEEE international conference on computer vision, pp. 2223–2232.

Zhu, P., Abdal, R., Qin, Y., Wonka, P., 2020b. Sean: Image synthesis with semantic region-adaptive normalization, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, IEEE Computer Society. pp. 5103–5112. doi:10.1109/CVPR42600.2020.00515.