DEVELOPING A TRAINING DATASET FOR DEEP LEARNING MODELS FOR APARTMENT LAYOUT GENERATION

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ABSTRACT

In recent years, there has been a rise in the development of automated apartment layout generation tools, demonstrating the increasing demand for resource efficiency and improved spatial organization in housing architecture. This study focuses on the apartment layouts from the Belgrade School of Housing (1960s–1980s, Yugoslavia), known for its exemplary architectural practices. The aim of this study is the creation and development of a dataset for training deep learning (DL) models for automated apartment layout generation. Given that many original layouts exist only in analogue format, the study introduces a protocol for dataset creation: (1) data collection and selection, (2) data digitization, (3) unified graphic language formation, (4) data augmentation, and (5) data compilation. The outcome of this study is a cohesive dataset for training and testing DL models, primarily Generative Adversarial Networks (GANs). Finally, the created dataset is tested through the apartment layout generation process. The main contribution of this study is a set of instructions for dataset creation that can facilitate data-driven design. This provides an opportunity for highly effective architectural concepts to be revived into a new design process powered by DL models. In future research, the universality of this dataset can be verified using different DL models.

KEYWORDS _ *Housing architecture, data-driven design, spatial layout generation, deep learning, training dataset*

INTRODUCTION

Spatial layout presents a fundamental aspect of residential architectural design. As it should meet various functional, aesthetic and user-specific requirements, the process of designing spatial layouts is inherently complex, iterative and time-consuming. Generative design, in general, is an iterative process of exploration and design supported by computational tools and generative algorithms, which enables the creation of various solutions (Bohnacker et al. 2012). Automated spatial layout generation (ASLG) emerged as one of the major fields in generative architectural design (Li et al. 2024).

Deep learning (DL) stands for computational models developed on artificial neural networks with multiple processing layers, which revolutionized artificial intelligence (AI). DL models are developed by training on ample and diverse data to learn patterns or rules within them for performing tasks they are designed for (Alpaydin 2020). Thanks to their capacities, various DL models, mostly generative adversarial networks (GANs), convolutional neural networks (CNNs), and lately, diffusion models, have been used in many studies in ASLG, creating synthetic data like architectural floor plans (Li et al. 2024). The studies utilize complex datasets for training and testing their DL generative models. Many factors besides the size of the dataset impact the training process (Alzubaidi et al. 2023). Hence, the issues of data collection, preparation, and augmentation should be addressed to form a proper training dataset. The lack of adequate data negatively impacts the adoption of DL models in many industries (Whang et al. 2022; Alzubaidi et al. 2023). While there are many studies on the use of DL models in ASLG, the process of dataset creation is usually neglected. Architectural spatial layouts, mostly in the form of floor plan drawings, are complex data containing various elements. It shows programmatic, geometrical and relational aspects which require a proper way of representation. In the case of architectural plans and similar data, one of the major problems is the lack of a digitized, vectorized archive. Many of the architectural drawings are only available in analogue format. This type of data varies additionally in terms of level of detail, graphic language, and the quality of the scan, if available.

The focus of this study is on the creation process of the dataset from existing apartment floor plans, for training a DL model to perform specific tasks in ASLG. This particular study is a part of broader ongoing research on the application of DL methods for apartments' spatial layout generation. In the study, a DL model is being trained for the task of generating a programmatic layout of an apartment out of given structural constraints as a conditional input. These structural constraints are recognized as a factor for enabling concepts of flexibility and adaptability of spatial organization. For this study, the data sample was narrowed to the spatial layouts of apartments built in Belgrade following the principles of the Belgrade School of Housing (BSH), a modernist thought in architectural practice, with its peak in the 1960s-1980s period. BSH is selected as one of its main principles is flexibility related to the structural system, especially skeleton frame structures with columns (Alfirevic and Simonovic-Alfirevic 2013). Hence, we address the question of how the dataset development for this specific DL model task is being conducted.

This study proposes the dataset development protocol – a set of instructions for the process that includes data collection and selection, digitization, data augmentation, and dataset compilation. The proposed methodology is aimed at providing balanced, consistent and high-quality training data for achieving higher efficiency of the DL model. The protocol is defined for the needs of the pix2pix GAN model, which requires paired data (Isola et al. 2018). This study resulted in the creation of a dataset utilized for training the DL GAN model for residential layout generation based on structural input. This paper contributes to the methodology of computer-aided architectural design, proposing a detailed protocol for data processing for DL model training.

FRAMEWORK

Automated spatial layout generation

Automated spatial layout generation (ASLG) originated in the 1970s, initially as a speculative artistic exploration of the future of architecture influenced by computers (Weber, Mueller, and Reinhart 2022). The ASLG methods are often seen in space planning or spatial composition synthesis. Over time, ASLG has utilized various generative algorithms such as shape grammars, biology-inspired algorithms (evolutionary and genetic algorithms), and case-based design tools (Sönmez 2018; Weber, Mueller, and Reinhart 2022). All these methods have been effective for straight-forward engineering tasks, but they struggle to perform efficiently for complex problems of spatial layout.

The emergence of artificial neural networks (ANN), drawing inspiration from biological neural networks, has significantly accelerated AI development. DL includes models based on deep ANNs, characterized by multiple processing layers, which enable processing of extensive data and execution of complex computational tasks (Alpaydin 2020). GAN models present one of the most effective algorithms for data synthesis. In GAN model, two neural networks, a generator and a discriminator, are trained in opposition: at first generator produces new data, then the discriminator attempts to distinguish between real and generated data (Goodfellow et al. 2014). Since their introduction, GAN models have found application in ASLG, as well as other architectural design tasks. Moreover, there is the application of other advanced DL models in ASLG, such as convolutional neural networks (CNN) and graph neural networks (GNN) (Ko et al. 2023).

Table 1: List of related papers on DL application in ASLG for residential architecture

Paper title	Authors	Input type	DL model	Pub. year
Architectural Drawings Recognition and Generation through Machine Learning	Huang and Zheng	images	GAN	2018
Data-driven Interior Plan Generation for Residential Buildings	Wu et al.	images	CNN	2019
House-GAN: Relational Generative Adversarial Networks for Graph-constrained House Layout Generation	Nauata et al.	graphs	GAN and Conv-MPN	2020
ArchiGAN: Artificial Intelligence x Architecture	Chaillou	images	GAN	2020
HouseDiffusion: Vector Floorplan Generation via a Diffusion Model with Discrete and Continuous Denoising	Shabani, Hosseini, and Furukawa	graphs	diffusion model	2022
Architectural layout generation using a graph-constrained conditional Generative Adversarial Network (GAN)	Aalaei et al.	images and graphs	GAN	2023

The dataset issue

DL models have entered many domains in recent years, with greater capabilities than old software packages. This fundamental paradigm shift in software engineering, where data-centric AI becomes the center topic, leads to new software powered by big data and computing infrastructure (Whang et al. 2022). DL models utilize large amounts of data during the training process to ensure their efficiency to learn patterns, while data diversity enables generalization to new instances. However, acquiring high-quality, diverse and ample training data can be a time-intensive, challenging and costly process, particularly in specialized fields (Talaei Khoei, Ould Slimane, and Kaabouch 2023). Stonebraker and Rezig (2019) claim that many research organizations tend to spend 90% of their machine learning efforts solely on algorithms and only 10% on data preparation, although it should be the other way, as they spend 90% of time on obtaining and processing data and only 10% on algorithms.

The problem of data scarcity for training algorithms stands as a major barrier, leading to small adoption of DL methods in many industries (Whang et al. 2022; Alzubaidi et al. 2023). Moreover, there are other issues regarding data, such as data bias, inconsistency, data poisoning, and data labeling. To overcome dataset issues in DL, new techniques are being developed. In the study conducted by Alzubaidi et al. (2023), several requirements for achieving trustworthy datasets are proposed: quality of data, annotation quality, diversity, size, source, preprocessing, balance and bias-free.

Dataset challenges occur in the architecture field, particularly for the residential spatial layout. There are several datasets containing apartment floor plans available for training DL models for ASLG. The most utilized dataset is the RPLAN dataset consisting of actual residential floor plans, obtained by Wu et al. (2019). There are also studies utilizing their own datasets - Huang and Zheng (2018) obtained 115 apartment floor plans for their dataset, and Chaillou (2020) assembled over 700 residential floor plans. According to Guo & Cui (2024), in the studies of DL applications in ASLG, the inclusion criteria, such as the design principles or detailed floor plan incorporation methods, for the training set are often neglected. Furthermore, they found that much existing research lacks a survey of the impact of training results on generated results. For such tasks, data consistency in the training process must be considered. Samples with diverse design principles within existing datasets like RPLAN might render the training set size increase ineffective for enhancing model performance (Chen 2022). In the field with a long tradition such as architecture, having a large amount of real-life data, the lack of data digitization remains a major issue.

METHODOLOGY (PROTOCOL)

The protocol for dataset development is proposed according to the requirements of training a DL model called pix2pix. Introduced in 2018, pix2pix is a general-purpose algorithm for image-to-image translation tasks, based as a conditional GAN (cGAN) (Isola et al. 2018). It is developed to learn the function of mapping features from an input image to an output image, as both generator and discriminator receive conditional input. The conditional setup provides the generation of output images directly related to the proposed input images.

The protocol – a set of instructions – for dataset creation consists of five phases: (1) data collection and selection, (2) data digitization, (3) unified graphic language formation, (4) data augmentation, and (5) data compilation. Eventually, GAN model is trained with dataset developed following this protocol. A qualitative analysis of training dataset is conducted based on requirements that data should meet to be trustworthy for deep learning models, defined in the study by Alzubaidi et al. (2023).

Data collection and selection

In the initial phase of dataset creation, sources containing apartments' architectural plans, from the period of BSH in the latter half of 20th century, are found. Relevant documentation was sought at the library of University of Belgrade – Faculty of Architecture, as well through online searching of sites focusing on architecture in Serbia. A notable resource presents the website of Do.co.mo.mo Serbia, hosting diverse documentation on modernist heritage in Serbia ("Do.co.mo.mo Србија," n.d.). Do.co.mo.mo Serbia operates as the national branch of an international working group dedicated to documenting and conserving architectural and urban heritage of the modernist movement. The collected sources include journals such as *Arhitektura Urbanizam*, the *Bulletin of the IMS Center for Housing*, and apartment catalogs from the IMS Center for Housing (referred to as the "*Fototeka stanova*").

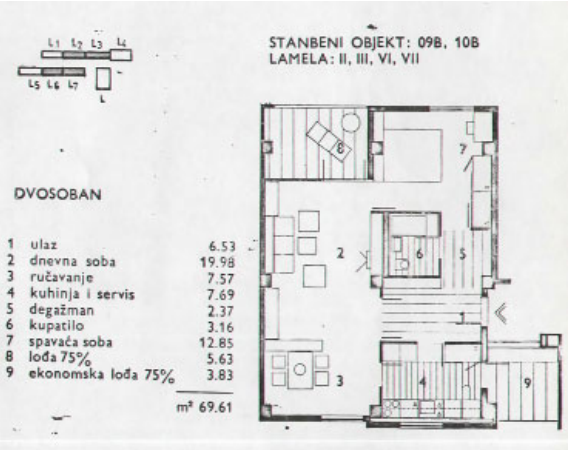


Figure 1: Apartment floor plan in Blocks 61-64, designed by architects M. Marušić, D. Marušić and M. Miodragović. Source: (Đorđević 1980)

The primary selection criterion is the structural system utilized within these residential buildings, due to the predefined research subject. Apartments with skeletal structures, mostly constructed with IMS prefabricated construction system, are selected. The architectural competition was organized for the most efficient structural grids for apartments with this system, demonstrating their consideration of structural constraints for residential spatial layout (Trbojević 1965). To expand the dataset, several apartments with load-bearing walls, transformed to skeleton frame structures, are added. A uniform selection of apartments with different sizes and layouts is conducted, with the requirement of at least one bedroom. Larger apartments (two or more bedrooms) inherently feature more complex spatial layouts. Equal distribution of diverse apartment layouts in the dataset intends to enhance model efficiency and reduce bias. All apartments include open spaces (terraces).

Data digitization

The selected pix2pix model requires paired and labeled data for training. Thus, two subsets are created in parallel: (1) the input subset representing the structural layouts, and (2) the target output depicting the desired function apartment layouts that adhere to the apartment's geometry and structure in the corresponding input. The digitization process, i.e., the vectorization of residential floor plans, was performed manually using Autodesk AutoCAD software. This process required precise dimensional coordination. Since dimensions were not included in a portion of the collected floor plans, an alternative method of dimensional analysis is applied. Having the standardized spans of the IMS system, either 3.60 or 4.20 meters, derived from a 60 cm base module, as well as the apartment equipment designed according to the same module, it is largely possible to determine the apartment dimensions with sufficient accuracy.

To enhance model training efficiency, floor plans are refined, eliminating unnecessary elements that could burden the training process. Key elements required for performing the proposed task were included in both subsets: apartment boundary, columns, and entrance position. In the input subset, structural grid and "blind" facades (walls without façade openings) were marked. In the output subset, the next elements are included: rooms labeled by function, interior walls, and openings. Though furniture and equipment elements were initially vectorized, they are excluded for the simplification of floor plans.

Unified graphic language formation

To ensure data consistency, a unified graphic language was defined. As mentioned in the previous section, the floor plans need to be clean, free of unnecessary elements. Structural columns, due to their key role as conditional input for floor plan generation, are depicted with the highest visual contrast. Except for the entrance position mark, which is painted red, the input drawings are monochrome. The drawings within the target output subset include areas filled with various colors to enable recognition of rooms. The façade and interior walls were differentiated by thickness. Figure 2 shows an example of input and output data, with graphical parameters for each element.

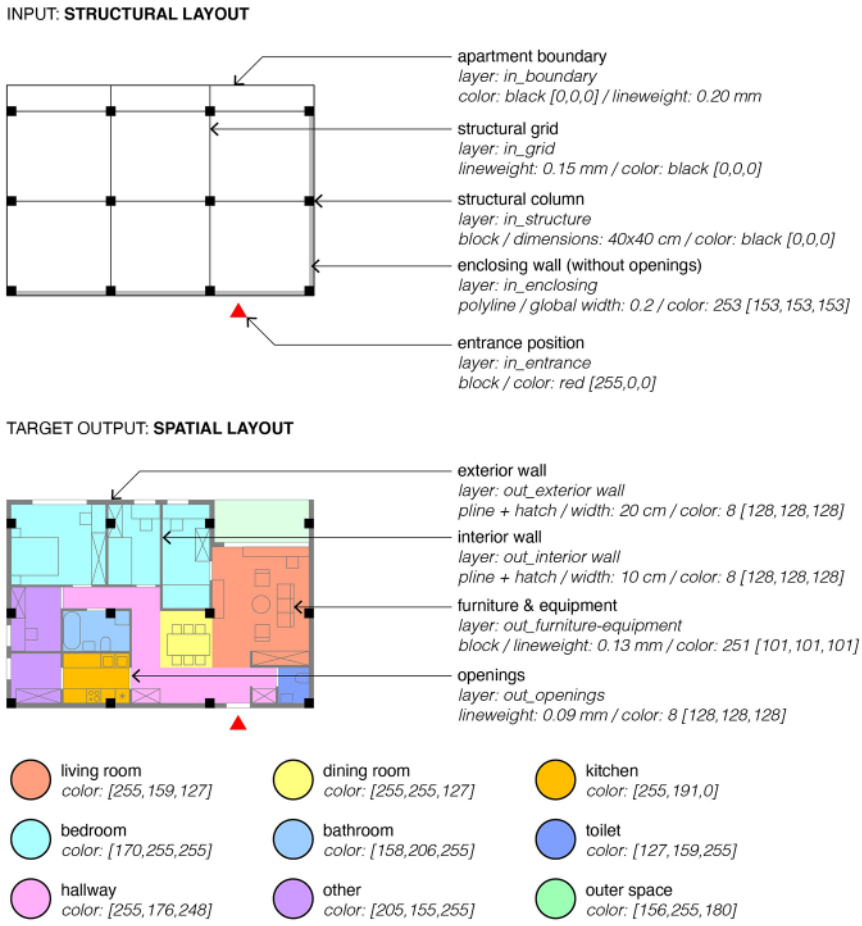


Figure 2: An example of input and target output data with graphical processing parameters for each element. Source: authors.

Data augmentation

In this phase, a series of modifications are carried out on several levels – geometric, spatial, structural, and graphical. Certain geometric modifications were necessary – their footprints are slightly redefined to simplify apartment floor plans. Having several apartments with load-bearing walls, they are transformed into skeletal structures with columns. Modifications are also made to align columns with walls or to adjust the position of terraces with the structural grid.

Since adaptability and flexibility of residential spaces are important aspects of this research, new spatial layouts are proposed for apartments with the same structural grid and boundary. Moreover, we proposed several residential spatial layouts based on a structure with larger spans. Thanks to this extra data in the dataset, the model can learn to generate alternative solutions. Finally, to expand the dataset, standard image transformations, such as mirroring and rotation, were applied, commonly used for data augmentation in other image generation models.

Dataset compilation

This represents the final step in the dataset creation. The training dataset for the selected model must consist of paired data – two images representing the input and the target output, each in a square format. The input and the output drawings are placed in the center within a square frame. Drawings from both subsets are separately exported to PDF format, then converted to JPG images. During the training and testing phases of the pix2pix GAN model, the translation direction (input to target output: A to B or B to A) can be configured. Corresponding drawings are paired using a Python script, ensuring that the input appears on the left (A) side and the output on the right (B) side. While the algorithm nominally requires a 256x256 px resolution, the original image resolutions remain, as resizing could be managed during model configuration.

RESULTS AND DISCUSSION

The final base consists of 34 pairs of residential spatial layouts with their corresponding structural layout. A number of 30 pairs are chosen for the training dataset, while the remaining four are utilized for testing the model. Image transformations – 90-, 180- and 270-degree rotation counter-clockwise – are applied to expand the dataset. Thus, the final training dataset consisting of 120 pairs is created.

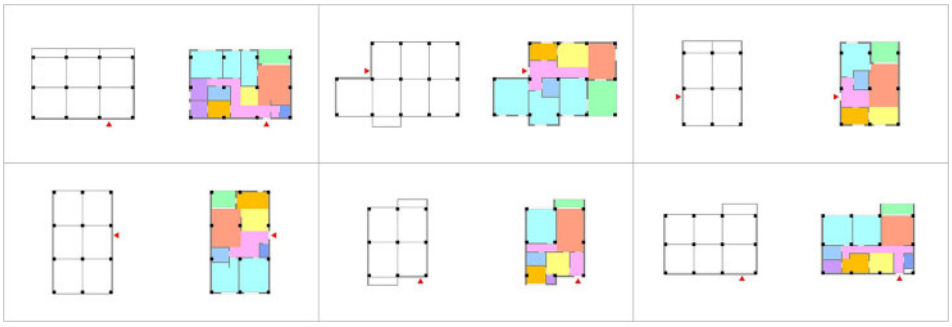


Figure 3: The part of training dataset showing input–target output pairs. Source: authors.

This dataset is utilized for training of pix2pix GAN model to perform residential layouts generation tasks. The training process is set up and run in Google Colab, a cloud-based notebook for executing computational tasks. The model training is executed using an NVIDIA T4 GPU, enabling a swift training process. The model is trained for a total of 500 epochs. Results of model testing are shown in Figure 4.

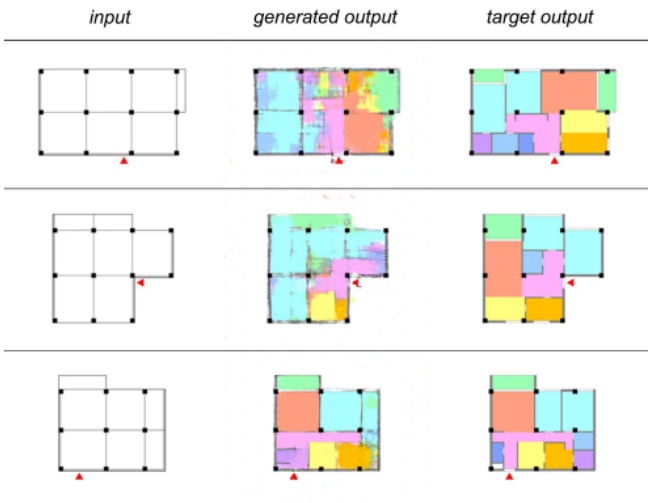


Figure 4: Results of testing of pix2pix DL model trained with prepared dataset. Source: authors.

We conducted the qualitative analysis of the training dataset of aspects presenting requirements for dataset trustworthiness for deep learning.

- **Quality of data**: This dataset contains image pairs of corresponding spatial layouts that are related to the designated task that the DL model should perform. The input data depicting structural layout is directly derived from the target output depicting the spatial layout of the apartment, which contributes to the GAN model's capability to extract rules of translation. These layouts are produced on the basis of collected floor plans of actual apartments. This potentially enhances the model's performance of executing practical tasks for spatial layout design.
- **Annotation quality**: All drawings of spatial layouts are produced in CAD software with technical precision. Each element has defined unique dimensional and graphical parameters to achieve clarity and non-ambiguity of plans.
- **Diversity**: In terms of apartment's size and program structure, there are various types in this dataset, from small apartments with one bedroom to large apartments with more complex spatial layouts. There are mostly rectangular footprints of apartments. On the other hand, the dataset contains smaller structural spans, lacking larger spans that are more common nowadays.
- **Size**: The training dataset size is extremely small, containing only 30 unique pairs of plans. The dataset was expanded by image transformations (rotations), eventually consisting of 120 pairs. With this size of dataset, the model can partially learn to generate, but the generated results are of poor quality. The image transformations do not enhance DL performance. For a better model's performance, it must utilize a larger dataset.
- **Source**: The obtained floor plans for dataset formation are found in reliable sources such as the University's library or the website of Docomomo Serbia, which is dedicated to the documentation and conservation of modernist heritage. Found documents are mostly acclaimed architectural journals of that time or official catalogues published by relevant institutes for housing architecture.
- **Preprocessing**: All data used for training was thoroughly processed, following the defined set of instructions. It includes vectorization, graphical unification, and several modifications to achieve uniformity and clarity. This enhances data usability, which is proven in early epochs of model training. However, processing is conducted manually, which makes the whole process very slow.

- **Balance**: We strived to make an equal distribution of apartment spatial layouts in terms of size and programme. The consistency of data is achieved through modifications in the preprocessing phase.
- **Bias-free**: Due to the smaller size of the training dataset and its lack of various spans and footprint geometries, the GAN model tends to be biased towards smaller spans, leading to generalization of spatial layouts in new scenarios. It still performs low efficiency in generating appropriate spatial layouts with larger spans or more complex geometries as input.

Here it is shown that consistent and balanced dataset, as a result of thorough preprocessing of data, improves model learning ability. However, the dataset size still presents a significant role in model's efficiency. These limitations of size are related to limitations of manual nature of preprocessing, which requires much time. To avoid bias of dataset, it should include more apartments from different periods and utilizing variety of spans.

CONCLUSIONS

This research develops and implements a protocol for dataset creation to facilitate DL based apartment layout generation. The methodology encompasses data collection and selection, digitization, unified graphic language formation, data augmentation, and compilation, providing a structured approach for transforming analog architectural drawings into machine-readable datasets. By focusing on BSH examples, we have demonstrated how historically significant architectural practices can be preserved and reintroduced through computational design techniques.

The primary contribution of this study is the creation of a comprehensive framework that enables data-driven design processes in architecture, specifically addressing the challenges of digitizing analog floor plans and standardizing them for deep learning applications. Testing confirms that the dataset effectively supports the training of GAN model for layout generation tasks based on structural constraints. There are three directions of future research: (1) expansion and diversification of dataset; (2) automation of data formation process, and (3) verification of universality of dataset using new DL models.

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APPENDI: The dataset is open-source and can be downloaded here: https://drive.google.com/drive/folders/1kibNB6YhEGnSwYNyZXxNs9QlRR2pZyHR?usp=sharing

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