A MACHINE-LEARNING APPROACH TO URBAN DESIGN INTERVENTIONS IN NON-PLANNED SETTLEMENTS

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Abstract. This study presents generative adversarial networks (GANs), a machine-learning technique that can be used as an urban design tool capable of learning and reproducing complex patterns that express the unique spatial qualities of non-planned settlements. We report preliminary experimental results of training and testing GAN models on different datasets of urban patterns. The results reveal that machine learning models can generate development alternatives with high morphological resemblance to the original urban fabric based on the suggested training process. This study contributes a methodological framework that has the potential to generate development alternatives sensitive to the local practices, thereby promoting preservation of traditional knowledge and cultural sustainability.

Keywords. Non-planned Settlements; Cultural Sustainability; Machine Learning; Generative Adversarial Networks; SDG 11.

1. Introduction

Informal and non-planned settlements are highly complex and typically develop through small-scale, bottom-up actions. Accordingly, their morphology is a result of environmental factors and reflects their specific social structure, economy, traditions, and cultural values (Habraken, 1998). Often regarded as chaotic and non-functional, these settlements present a unique challenge to urban design practitioners and policymakers (Schaur, 1991). Adequate solutions to the substandard living conditions in non-planned settlements require a deep understanding of their initial formation and expansion processes and appropriate tools to evaluate potential policies or interventions (Patel et al., 2018).

To address this challenge, in this study, we present a machine-learning (ML) and computer vision approach that can be used as an urban design tool. We demonstrate a ML model trained to learn and reproduce the complex urban patterns of the town Jisr az-Zarqa in Israel, expressing the unique spatial qualities of this settlement. The lack of consistent planning policy in rural Arab settlements in Israel (Brawer, 1994) led to

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unplanned development of Jisr az-Zarqa which, until 1988, had no official master plan (Israel Land Authority, 1992).

We argue that applying Artificial Intelligence (AI) to the design practice can be valuable due to its ability to learn urban patterns that resulted from dynamic and spontaneous self-organization processes. Therefore, AI tools can be meaningfully used by professionals, policymakers, and local communities to better visualize and reflect on the potential outcomes of different development scenarios. Moreover, AI tools can generate design solutions that are not merely imitating local forms but are also sensitive to the local culture and contributing to the promotion of more sustainable communities.

In this study, we contribute a generative machine-learning method to produce complex urban morphology and generate multiple alternatives as design recommendations, based on Pix2PixHD model (Wang et al., 2018).

The remainder of this paper is structured as follows. In Section 2, we briefly review relevant previous studies that used different approaches to investigate informal settlements. The methodology used in the present study is described in Section 3. In Sections 4-6, we present the process and the results of training our model on different data, testing it, and then using it to generate new alternatives for the urban fabric. The results are summarized and discussed in Section 7.

2. Related Work

Relevant approaches used in research on informal settlements include agent-based modelling (ABM), shape grammar, and, more recently, machine learning.

Agent-Based Modelling (ABM) is a method used to simulate bottom-up processes to predict urban development. In these simulations, decision-makers are represented as agents capable of responding to their environment and taking autonomous action. For instance, Patel et al. (2018) suggested a model that integrates agent-based modelling with Geographical Information System (GIS) to provide a platform for studying the emergence of slums. The authors argued that this model is helpful for testing slum policies before applying them in real-life settings. Likewise, Patt (2018) explored the applications of the ABM approach to urban redevelopment in informal contexts, with a particular focus on the public space network as the primary object of the multi-agent model.

The shape grammar approach defines initial shapes and a set of transformation rules applied to describe architectural evolution over time. For instance, using the shape grammar approach, Verniz and Duarte (2017) described the evolution of an informal settlement of Santa Marta in Rio de Janeiro and predicted future growth of this informal urban fabric. Similarly, Ena (2018) explored the potential use of shape grammar to regularize the favelas in Rio de Janeiro and better understand spatial ideas and politics behind their architecture.

However, a limitation of both ABM and shape grammar is that these two approaches depend on the assumptions resulting from an analysis of settlements or comprehension of individuals' dynamics and decision-making processes. Yet, the complexity of non-planned settlements makes this a challenging and time-consuming task.

In this context, considering that artificial neural networks can be trained to

recognize highly complex patterns, thus allowing design professionals to focus on the evaluation and decision-making phase, the machine learning (ML) approach becomes particularly relevant. Several previous studies proposed using a specific ML method called Generative Adversarial Networks (GANs) to design urban blocks. More specifically, Yao et al. (2021) used a GAN model pix2pix to generate plot layouts of varying building densities based on similar settings in Shanghai and further evaluated them using Octopus and Ladybug simulations. Furthermore, Fedorova (2021) suggested using GANs to design urban blocks of several European cities based on the surrounding morphology. These methods were applied to planned urban fabric dictated by local policies, masterplans, and regulations. In the next section, we explain how we applied a similar approach to generate a complex urban morphology of a non-planned settlement.

3. Methodology

In this section, we describe the ML model used in the present study, the methods we used to generate training datasets, testing the trained model, using it to generate new urban morphology and evaluating the results.

3.1. MACHINE LEARNING

Artificial Neural Networks (ANNs) are computer software modelled after the metaphor of neurons in brains interconnected by synapses. Each neuron receives several inputs and computes an output. The connection between two neurons, called an edge, has a particular weight that influences the specific information transferred. ANNs made of several layers of aggregated neurons are called deep neural networks. When an ANN receives an input, it is processed by the neurons and the ANN generates an output. The main feature of ANNs is their capability to be 'trained' to adapt their output. For a more accurate output, the neurons' computational functions and edges' weights are modified during the training process.

In the present study, we used Pix2PixHD, a deep learning method that can synthesize photorealistic images from semantic label maps using conditional Generative Adversarial Network (cGAN) (Wang et al., 2018). A GAN is a system consisting of two deep networks—the generator, which generates an output, and the discriminator, which identifies whether or not the generated output is similar to the requested output. GANs are useful since they can be trained based on a dataset in an unsupervised way. In contrast to a regular GAN, a cGAN is a specific kind of GAN that receives an input. Several previous studies used similar methods to explore the utility of the ML method for urban and architectural plans generation (Fedorova, 2021; Ye et al., 2021; Chaillou, 2020).

3.2. TRAINING DATA SET

One of the challenges associated with creating an ML model is the large amount of data required for unsupervised training. Specifically, producing a large quantity of map images for each dataset can be highly time-consuming. Therefore, an efficient method to generate large amounts of data will increase accessibility of the suggested model to practitioners.

In the present study, we selected ArcGIS for data set extraction since it has a relatively accurate mapping of Jisr az-Zarqa. Furthermore, we leveraged ArcGIS's integrated Python scripting option and created a "map extraction tool" (MTRL

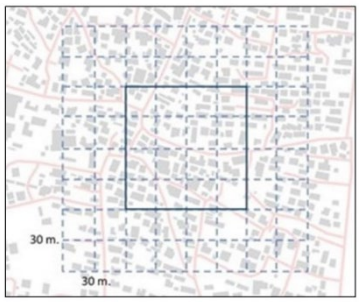

Figure 1. Jisr Az-Zarqa – map of the town including its building masses (black) and roads (red). The map is divided into a grid of 30m offset. (Credit: MTRL 2021, Technion IIT)

Technion IIT, 2021) that automatically exported maps in JPEG format (see Figure 2a, 2b). Using the Python script, we generated a total of 220 map tiles that were sufficient for training the GAN. The initial extent and scale of the first tile were defined, and the subsequent tiles were automatically exported with an offset of 30 meters on the X and Y coordinates until the entire area of the town was covered (see Figure 1).

3.3. EVALUATION

Upon completion of the training process, we tested the model on map images that were not included in the training set. To evaluate the success of the trained model, the test results were compared visually to ground-truth maps of the settlement in terms of urban structure and patterns. The complexity of non-planned urban fabric can be addressed through multiple aspects; however, the current study focuses solely on morphology. Since the data for the presented experiments is highly simplified, representing limited morphological information, the selected evaluation criteria were also limited to four basic characteristics- the model's ability to a) continue existing roads and suggest new ones, b) recognize topological features of the street network, c) reproduce building morphology with similar density and d) reproduce similar building typology. Topological feature of the street network refers to the linking of different elements, thus the number of streets that meet at each intersection. Density refers to the number of buildings per given area and building typology refers to the shape and area of the building masses.

3.4. SOFTWARE AND HARDWARE

The model was trained on a computer with a 12 core, 3.6GHz CPU with 32GB of memory and an Nvidia Quatro RTX 5000 graphic card. The computer's operating system was Ubuntu 20, and we installed the Python scripts using Anaconda. Pix2pixHD was retrieved from Wang et al. (2018).

In Sections 4-6, we report the results of three studies (Studies 1-3) where we trained

the Pix2PixHD model on different data, tested it, and used the results to generate new alternatives for the urban fabric of Jisr Az-Zarqa.

4. Study 1- Pilot

In Study 1, we aimed to train the model to complete a partial map image with patterns that would resemble the existing morphology of the Jisr Az-Zarqa settlement.

4.1. METHOD

A graphic layer of the Jisr az-Zarqa map was created based on ArcGIS's base map. The layer contained black outlined polygons as buildings and red polylines as roads and was exported as JPEG tile pairs using the map extraction tool. Each pair was made from a partially blank input map and a complete output map. To produce the input map, the output map was duplicated, and the right half was erased (see Figure 2b). Next, the model was trained for 200 epochs; the total duration of the training was ca. 36 hours. Finally, we tested the trained model using new input tiles and evaluated the generated outcome.

4.2. RESULTS

Figure 2c shows the results of the trained model after 200 epochs given the input in Figure 2b. As can be seen in the figure, the model failed to identify the buildings polygons as patterns in the current settings or to complete the missing urban morphology. The generated forms were distorted polygons, and the generated pattern did not fill the entire frame. These results highlight that it is not straight-forward to train a ML model to generate such patterns. Accordingly, we concluded that a different image labelling, with adjusted structure and colors, would be necessary.

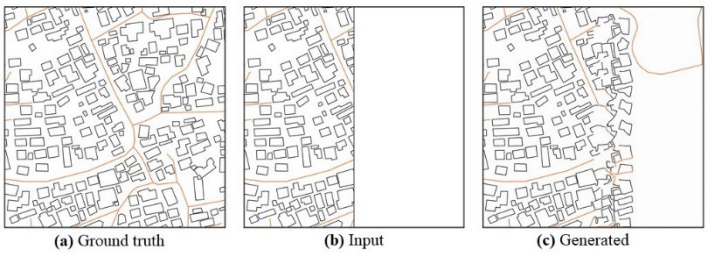

Figure 2. Study 1 - Test ground truth map tile of Jisr az-Zarqa (a), test input image (b), and generated output (c). In the process of training the model, tile (b) was used as input and (a) as output. (Credit: MTRL 2021, Technion IIT)

5. Study 2- Nolli Maps

Based on the results of Study 1, in Study 2, we repeated the training process using image labelling by creating a different dataset format. The new format provided a 360-degree context for the blank area and used a simpler image labelling.

5.1. METHOD

We generated a new simplified dataset using the map extraction tool. Compared to the approach used in Study 1, in this study, there were two main differences. First, we changed map labelling by replacing the building polygons with solid black polygons (like Nolli maps). We hypothesized that this adjustment would mitigate the corrupt polygons. At this stage, the red polylines of roads were removed. The second difference was changing the input map format—specifically, we erased a rectangle in the center of the image (instead of the right half as in Study 1). We hypothesized that providing a surrounding urban context would be beneficial for the completion of patterns over the required area. The size of the new dataset remained the same (220 tiles), and the model was trained anew, this time for a total of 300 epochs, which took approximately 48 hours to complete.

5.2. RESULTS

The results of Study 2 showed a significant improvement. Specifically, the model successfully learnt the existing urban fabric and completed the blank part of the map accordingly. The polygons were complete, and the model covered the whole area (see Figure 3c). The generated map produced a new pattern with a high morphological resemblance to its surroundings and to the ground truth. The newly filled area contained 40 buildings of mainly rectangular shape with the total built area of 5702 sqm, while the ground truth map contained 42 buildings with the total built area of 5865 sqm. In addition, the model was able to fill in the continuous roads which were not explicitly marked but were visible due to the broader spaces between the buildings.

(a) Ground truth **(b)** Input **(c)** Generated

Figure 3. Study 2—Nolli maps dataset. Ground truth (a), the corresponding input map (b), and the map generated by the trained model (c). (Credit: MTRL 2021, Technion IIT)

6. Study 3- Generating New Urban Fabric

The aim of Study 3 was three-fold: 1) to increase the complexity and size of the dataset; 2) use the trained model to generate multiple alternatives to a new urban fabric as an infill in an empty area of Jisr az-Zarqa; and 3) test the model on different settlements.

6.1. METHOD

The training process was repeated, this time on a higher-complexity dataset. The Nolli maps from Study 2 were used, the size and the scale remained the same. However, the roads layer was added again as red polylines. To avoid overfit, the dataset was enlarged from 220 tiles to 1100 tiles by rotation and mirroring of the original dataset.

Thus far, the model was found to be able to generate one single output for each input, even when tested on the same map multiple times. However, for ML models to become a potential design tool, they should be able to produce a variety of alternatives. To address this challenge, we tested the model on several input maps with a small offset (1 m) between each. This time, the blank area of the map included an empty area potentially suitable for infill intervention.

The same model was tested on two different examples—namely, Fureidis, an Arab town near Jisr az-Zarqa, and New York. Despite being located on much steeper topography, Fureidis shares some cultural and morphological similarities to Jisr az-Zarqa; accordingly, this test was run to identify whether the trained model can be applicable to other similar settlements. New York—which is a planned, orthogonal grid—was tested as an opposite example.

6.2. RESULTS

The results revealed that, after 500 epochs, the model successfully generated an urban fabric that morphologically resembled the existing patterns of Jisr az-Zarqa (see Figure 4c). The continuous roads were consistent with the ground truth, and the intersections were of the same topology—namely, three-armed intersections and dead-end streets. The building density was similar- 47 buildings vs. 44 in the ground truth, however the scale of the building masses was smaller- with total built area of 5997 sqm vs. 8748 sqm in the ground truth. This finding can be explained by the fact that this particular area is the commercial and the historical center of the town; therefore, it is the first to undergo a densification process. Since the model completed the blank part with patterns learned from the context, it reproduced the same building typology as the surroundings which to date are not considerably densified yet.

However, as shown in Figure 4f, the results generated for Fureidis were not as accurate. Specifically, the building density was lower- only 61 buildings with a total built area of 6012 sqm vs. 78 buildings with total built area of 9428 sqm in the ground truth. The generated roads were less consistent with the ground truth in terms of continuity, likely due to the different structure of Fureidis where topography plays a more significant role, a dimension which is currently not addressed by the model. Notwithstanding, the topology of the road network was partially preserved. Moreover, the model adapted the existing network to self-generated morphology- replacing a planned round-about with a three-armed junction. This trend becomes even more evident in the test results for New York (see Figure 4i): since the model was not yet familiar with continuous, orthogonal grids, the road network was transformed to become dead-end streets and 3-armed junctions. The missing building masses were completed according to the Jisr az-Zarqa morphology, and the model attempted to not just fill in the blank part of the map, but also to modify the surrounding context.

As the testing results of study 3 for Jisr az-Zarqa revealed that the model can reproduce urban fabric with similar morphological features, Figure 5 demonstrates several alternatives of new infill within an existing urban. The different outputs generated by the model had only a slight offset in the input maps. Such small offset enables the user to remain in the same surrounding context yet creates different settings for the model with a high degree of variation between the outputs in terms of building layout and additional or modified roads.

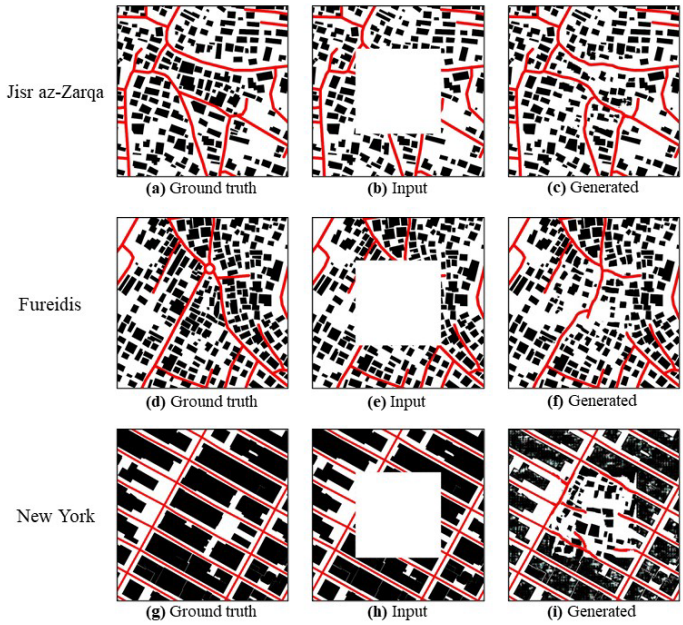

Figure 4. Study 3—Test results for the trained model. Upper row - Jisr az-Zarqa, middle row- Fureidis, bottom row- New York. Ground truth (left), input (center) and model output (right). (Credit: MTRL 2021, Technion IIT)

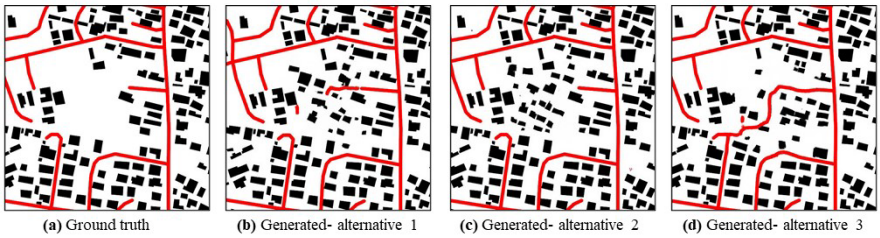

Figure 5. Study 3- An example of generating multiple alternatives (b-c-d) for a new infill fabric in Jisr az-Zarqa. (Credit: MTRL 2021, Technion IIT)

7. Discussion

7.1. MACHINE LEARNING FOR COMPLEX URBAN MORPHOLOGY GENERATION

The results of the present study revealed that machine-learning models hold great potential in the research and practice in informal and non-planned contexts. Unlike other popular approaches that require complex and time-consuming analysis, ML models are capable of learning local patterns and generating new outputs, as well as making adjustments in the existing fabric.

GAN models, specifically Pix2PixHD, are an effective method for urban design. An efficiently trained GAN model can reproduce a complex urban fabric of a non-planned settlement, with morphological resemblance of buildings and consistent topological qualities of the road network. The results of Studies 1-3 emphasize that the success of the ML approach largely depends on the quality of the training data. Specifically, we determined that good performance depends on distinct labelling, appropriate scale, and an appropriate balance between dataset size and training epochs in order to avoid overfit. In Studies 1-3, the best results were achieved at the scale of 1:2000, with dataset size of at least 1100 maps, and with 500 training epochs. In addition, we demonstrated that the trained model can be used in other settlements with similar morphology.

The ability to provide long-term sustainable solutions largely depends on the evaluation of the suggested policies and interventions. In this study, we presented a method to generate multiple output variations that allows professionals and the community to reflect on the potential outcomes of different scenarios as part of the design process.

7.2. LIMITATIONS AND FUTURE RESEARCH

While the presented method achieved the expected performance, it has several significant limitations in the broader scope of urban design. Since the model is two-dimensional, it cannot address topography, building heights, or three-dimensional visualization of the proposed layouts. Furthermore, as revealed by the results, it currently fails to generate new urban morphology without full context, such as a new extension to an existing settlement in an empty area. Furthermore, the proposed method cannot be adjusted to address design requirements, such as increased density, or minimal and maximal building sizes.

Accordingly, in order to improve the model's performance in practical applications, further research and development would be needed. Notwithstanding, the results of iterative series of experiments reported in this study contribute to establishing a methodological framework that can be used as a generative tool in informal contexts. Our contribution includes the production of datasets for training ML models, testing, and generating new urban layouts that can be further evaluated as urban design interventions.

To conclude, the proposed method can bridge the gap between top-down and bottom-up design practices and generate development alternatives that are sufficiently sensitive to the local communities, thus promoting preservation of traditional

knowledge and cultural sustainability.

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