MACHINE LEARNING TOOL FOR SUSTAINABILITY EVALUATION: 
THE CASE OF NEIGHBOURHOODS’ DESIGN

NOAM M. RAANAN1, HATZAV YOFFE2, GAL ZEEV3 and YASHA J. GROBMAN4
1,2,3,4Technion - Israel Institute of technology.
1noammraanan@gmail.com, 0000-0002-5499-6275
2hatzavy@campus.technion.ac.il, 0000-0003-0262-3052
3gal.zeev@campus.technion.ac.il,
4Yasha@technion.ac.il, 0000-0003-4683-4601

Abstract. This paper proposes a framework for machine learning to evaluate landscape design. In this study, we measured key performance indicators of landscape-development plans using a convolutional neural network (CNN) approach to predict the performance level of the design. The model used 3749 performance evaluations from 36 professionals, covering six sustainability criteria in 32 neighbourhoods’ designs. Results show a high agreement level between experts on the performance level of the designs. The study contributes to computational sustainability by showing the potential in evaluation-automation of urban resiliency, ecological enhancement, and design for wellbeing, using expert knowledge and machine learning.

Keywords. Urban Design, Landscape Architecture, Computational Sustainability; Machine Learning; Convolutional Neural Network; Landscape Sustainability; SDG 9; SDG 11; SDG 13; SDG 15.

1. Introduction
In the Anthropocene, the urban population grows on account of natural habitats (Almond, Grooten, and Peterson 2020). Urban sprawl, densification, and development on open land contribute to the ongoing degradation of existing ecosystem services in cities, which due to climate changes, results in severe urban ailments such as increased vulnerability to hurricanes, flooding, wildfires, and heatwaves. (SCBD, 2012). Sustainable urban landscape development that enhances ecologies and strengthens communities' resiliency is essential for adapting to climate change and increasing the well-being of urban dwellers (United Nations 2021). Although Sustainable design of buildings is considered a standard practice in the architectural engineering and construction (AEC) industry, sustainable design of neighbourhoods is still considered a labour-intensive, expert dependent, and time-demanding process with low implementation rates (Pedro et al. 2019). Recent technological advancements in Building information modelling (BIM) and Geo-design (Ayman, Alwan, and McIntyre 2020; Wang, Pan, and Luo 2019) promote automation, analysis, and visualization of sustainability performance in design, making computational sustainability an emerging
field of research (Chong, Lee, and Wang 2017). Integration of automation using machine learning (ML) methods that provide access to what were once tedious tasks, helps to reduce calculation and evaluation time. It also facilitates finding new relations between elements, for tasks such as energy simulations (Hendrycks, Lee, and Mazeika 2019; Sebestyen, and Tyc 2020), and classification of architectural building types using images (Date and Allweil 2021).

In urban landscape design, ML methods were used for tasks such as classification of buildings, land use and roof types, quality evaluation of building facades, visual quality of streets, and citizens’ perception of the built environment such as safety aspects, in growing numbers each year (Tebyanian 2020).

Although significant work has been undertaken in this area, there seems to be less focus on evaluating urban landscapes at the neighborhood level; specifically regarding sustainability aspects: design's social, ecological, and resiliency. (Yoffe, Plaut, and Grobman 2021). Furthermore, to our knowledge, none of the automation processes found in the existing literature uses expert-based evaluation datasets.

This study aims to advance computational sustainability by introducing a framework for sustainability evaluation using expert-based knowledge and machine learning. It also suggests a preliminary method that uses a convolutional neural network algorithm trained to evaluate the sustainability properties of plans based on expert-evaluation data collection.

This paper presents the proposed method and a demonstration experiment, covering 32 neighborhood development plans and 36 landscape sustainability expert evaluations, followed by a discussion of the experiment results.

2. Methodology

The proposed framework extracts domain experts' knowledge using a survey and translates it to sustainability KPIs. A machine learning-based approach implements the acquired knowledge to automate sustainability evaluation, supporting expert feedback input for the next design iteration (figure 1). The method was divided into three steps: (1) data collection via survey, (2) data analysis and preparation, and (3) computation method validation (Figure 2). The final training dataset included 3749 performance evaluations from 36 professionals, covering six sustainability criteria of 32 neighborhood designs.
2.1. STEP 1: DATA COLLECTION

Expert data was collected via a survey among landscape professionals. Experts rated six sustainability criteria in 32 rendered neighborhood plans. Neighborhoods plans, randomly selected from a web image platform (see Figure 3). Word combination used in image search included: 'urban development', 'neighbourhood', 'landscape design'.
neighbourhood plan', 'landscape plan'. We choose plans similar in development level and rendering style. Also, plans had similar architectural elements, such as buildings, streets, and vegetation. Chosen plans had no text labelling, an indication of their location or origin, or any other form of information besides graphics.

Three sustainability aspects were evaluated: ecology, resilience, and society, each containing two key performance indicator (KPI) criteria. The achievement level for each criterion was described on a scale of 1 to 7 (Table 1). The choice of KPIs was based on local AEC industry needs for evaluating ecological, social, and resilience design aspects in landscape development (Yoffe, Plaut, and Grobman 2021).

<table>
<thead>
<tr>
<th>Sustainability criteria (KPIs)</th>
<th>Evaluation description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ecology</strong></td>
<td></td>
</tr>
<tr>
<td>Vegetation patch connectivity</td>
<td>Does the design and dispersion of vegetation encourage fragmentation or connectivity (based on trees and streams)? (1) fragmented, (7) connected</td>
</tr>
<tr>
<td>Vegetation patch diversity</td>
<td>Does the design create similar (1) or diverse (7) spaces and outdoor experiences?</td>
</tr>
<tr>
<td><strong>Resilience</strong></td>
<td></td>
</tr>
<tr>
<td>Urban heat island (UHI)</td>
<td>How much, to your opinion, does the landscape mitigate the urban heat island effect and encourage moderated micro-climate? (the evaluation of UHI is determent by the ratio between hard surfaces and soft surfaces, SRI of surfaces, and the dispersion of landscaping and vegetation). High mitigation (7), Low mitigation (1)</td>
</tr>
<tr>
<td>Stormwater management</td>
<td>How much, to your opinion, does the design (dispersion of open spaces) enable implementation of stormwater management methods (retention areas, blue roofs, etc.) and decrease of flooding damages? Very poor (1), Very well (7)</td>
</tr>
<tr>
<td><strong>Social</strong></td>
<td></td>
</tr>
<tr>
<td>Exposure to nature</td>
<td>How much, to your assumption, does the design expose the residents to the environment and the natural components in the design? Low exposure to none (1), High exposure(7)</td>
</tr>
<tr>
<td>Walkability</td>
<td>Does the design encourage a safe and comfortable walk between the neighborhood points of interest (enables continuous walk, shade, interest, multiple walking possibilities)? Doesn't encourage walkability (1), Highly walkable and connected (7)</td>
</tr>
</tbody>
</table>

Table 1: Sustainability aspects and evaluated criteria.
Figure 2: Examples of rendered plans from the survey
Each neighborhood was represented by a plan image (Figure 2), followed by the sustainability evaluation questions. The survey was distributed to the professional landscape community during the 18th annual Israeli Association of Landscape Architects (ISALA) meeting and conference.

2.2. STEP 2: DATA PREPARATION

Data preparation included determining the agreement level between experts and cataloging the neighborhood plans for computational ML training. Data preparation had two goals: to determine consistency and to determine agreement. After normalization of the evaluation results, consistency was calculated using Cronbach's alpha equation for each criterion on all 32 neighborhoods. We defined consistency as coefficient $\alpha > 0.70$ as it is an accepted benchmark by many studies in the social studies field (Cortina, 1993). Agreement among experts was found by calculating the standard deviation of each criterion.

2.3. STEP 3: COMPUTATIONAL MODELLING

The final step included exploring sustainability evaluation using machine prediction. This study scope examined the KPI with the highest expert agreement rating, meaning the lowest standard deviation (figure 3). We chose the 'Vegetation patch diversity' criterion, aiming to test all six KPIs in the future.

The neighborhoods were divided into three achievement levels: high, medium, and low based on the average normalized score in the specific criteria where low $< 0.33$, medium $< 0.66$, and high $> 0.66$. The ML model architecture is a convolutional neural network [CNN] used in small data learning experiments like Chollet (2016). The script was written using the Keras and Tensorflow libraries. The algorithm included an augmentation stage where each neighborhood image was randomly rotated, flipped, scaled, and shifted to create more training data. Overall, the model created an additional 20 training images from each image. Following augmentation, data was split into train and validation sets, creating two directories, a test directory containing 625 images and a validation directory with 155 images, a customary ratio of 80-20. Finally, each of the folders was split into three (3) subfolders based on the overall score received by the experts.

Figure 3: ML model included five convolutional blocks, divided into 16 batches and 30 epochs.

The model architecture consists of five convolutional blocks (figure 4). The data was divided into 16 batches for a training run with 30 epochs. Adjustments were made
in the last fully connected block after each run to try and achieve better accuracy until reaching the best performance with the available toolset.

The study scope tested the prediction accuracy of computer analysis for one sustainability KPI as a proof of concept.

3. Results

The professional survey showed promising results regarding consistency and agreement between experts, from similar backgrounds, for visual evaluation of sustainability aspects of plans (Table 2).

The survey results showed high consistency in participant evaluations (coefficient $\alpha >0.80$) in all evaluated participants. Participant evaluation numbers varied for each criterion due to the incompletion of the survey, resulting in a range between 9-11 participants used to measure Cronbach's alpha for each KPI.

Like consistency, agreement levels – average standard deviation, were in an accepted range between 0.19-0.23, meaning experts agreed on the performance level of the neighborhood by visual analysis only (Table 2). In addition, the coefficient of variant across all KPIs was less than one, meaning a strong similarity in answers between different experts (Table 2).

The results achieved by the ML algorithm for measuring vegetation patch density were low with an overall average accuracy of 13.5% and could not be considered a successful prediction. This might be explained either by insufficient modeling data amounts, by the architecture of the CNN model in interpretation of the neighborhoods or a combination of both.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>n</th>
<th>$\alpha$</th>
<th>ASD</th>
<th>CoV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resiliency</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban heat island</td>
<td>n = 11</td>
<td>0.80</td>
<td>0.19</td>
<td>0.59</td>
</tr>
<tr>
<td>Stormwater management</td>
<td>n = 9</td>
<td>0.87</td>
<td>0.22</td>
<td>0.71</td>
</tr>
<tr>
<td>Ecology</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vegetation patch connectivity</td>
<td>n = 9</td>
<td>0.92</td>
<td>0.22</td>
<td>0.78</td>
</tr>
<tr>
<td>Vegetation patch diversity</td>
<td>n = 11</td>
<td>0.86</td>
<td>0.19</td>
<td>0.53</td>
</tr>
<tr>
<td>Social</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exposure to nature</td>
<td>n = 10</td>
<td>0.86</td>
<td>0.21</td>
<td>0.62</td>
</tr>
<tr>
<td>walkability</td>
<td>n = 9</td>
<td>0.89</td>
<td>0.23</td>
<td>0.57</td>
</tr>
</tbody>
</table>

Legend: $n$ - number of experts used for $\alpha$, $\alpha$-Cronbach's $\alpha$, ASD - average standard deviation, CoV-coefficient of variation
4. Discussion and conclusions

This study introduced a framework and a method aimed at connecting expert knowledge on sustainability with computational evaluation using ML abilities. The suggested method uses a CNN algorithm trained to evaluate the sustainability properties of plans, based on an evaluation dataset, achieved using a survey among landscape sustainability experts.

The study demonstrated positive results in the agreement level between expert evaluations of neighborhood plans. It strengthened the idea that domain experts agree on the sustainability performance level when evaluating projects. This ability, which captures the qualitative evaluations and transforms them into quantitative data, is the cornerstone for useable datasets in ML-based tools. However, the low prediction results of the applied CNN tool highlight the importance of increasing the sustainability evaluation datasets prior to the successful application of this method by practitioners.

Machine learning in urban and landscape design is an emerging and rapidly growing field (Yoffe, Plaut, and Grobman 2021). In a literature review done by Tebyanian (2020), out of 71 papers reviewed, 34 were published in 2019 and 15 in 2018, portraying this phenomenon. Not only the academy is looking towards ML methods but practitioners as well. The American Society of Landscape Architecture (ASLA) (2019) shows that more than 25% of landscape architecture firms intend to adopt AI/ML as part of their arsenal of tools, motivating researchers and reassuring that studies like this have a place in the frontlines of landscape architecture computation.

The proposed method has successfully demonstrated a workflow for utilizing domain-expert knowledge to advance the design process by disseminating sustainability evaluation abilities to non-professionals. However, the scope of the data gathered was not sufficient to achieve high computation prediction rates.

Future studies which would extend professional datasets and the measured sustainability criteria can significantly contribute to the implementation of sustainable design in ongoing and planned developments. Introducing ML automation to sustainability evaluations could help a labor-intensive become broadly accessible to the AEC industry and support global efforts in creating ecologically rich, resilient environments and more liveable cities.

Acknowledgements

We would like to thank the Israeli Association of Landscape Architects ISALA, especially to Michal Bitton, for helping disseminate the survey during the 18th ISALA Expo and Meeting. Rendered plan images courtesy of the Commons Landscape Design Studio, Lerman Architects, Lavi Natif, Engineering and Consultants Ltd., Arim Urban Development Ltd., iStern Project Management, Shikun & Binui, Moshe Zur Architects & Town Planners Ltd.
References


