Evaluation of Urban Perception Using Only Image Segmentation Features

Xinyi Li[a], Benjamin Beaucamp[b], Vincent Tourre[c], Thomas Leduc[d] and Myriam Servières[e]
Nantes Université, ENSA Nantes, École Centrale Nantes, CNRS, AAU-CRENAU, UMR 1563, F-44000 Nantes, France

Keywords: Urban Perception, Voluntary Geographic Information, Place Pulse 2.0, Computer Vision, Panoptic Segmentation, Deep Learning, Machine Learning.

Abstract: Deep learning has been used with the street-view imagery Place Pulse 2.0 to evaluate the perception of urban space along six perceptual dimensions: safe, lively, beautiful, wealthy, boring, and depressing. Traditional methods automatically extract feature representations from images through a convolutional neural network to yield prediction. However, the formers are computationally intensive and do not take a priori into account the semantic information from panoptic segmentation scene. In light of this, we propose that learning with semantic information could be close to full image analysis for the prediction of perceptual qualities. A lightweight solution is presented, which quickly predicts the sense of urban space from the implied highly compressed segmentation feature vectors of the street-view images via deep/machine learning models. Our solution achieves an average accuracy of about 62%, which is acceptable compared to the baseline result accuracy of 68%, and significantly reduces the complexity of the data and the computational effort.

1 INTRODUCTION

The physical appearance of urban space could affect the perception of individuals (Azma and Katanchi, 2017), and further influences their behavioral patterns (Miranda et al., 2021). Many social scientists have revealed the link between the disorderliness of cities and residents' perception of safety and criminal behavior (Kelling et al., 1982), between the appearance of street buildings and the feeling of fear and health (Cohen et al., 2003), between neighborhood perceived climate and education (Milam et al., 2010), etc. Objectively evaluating the impact of urban landscape on residents' perception is of great importance to effectively analyze and predict residents' behavior patterns, and inspire urban planners and decision-makers on the improvement of urban life quality. One application of this research by (Zhang et al., 2018a) is the creation of a map showing the spatial distribution of the sense of safety perceived through the streetscapes in Chengdu. Their work can reveal to urban planners which areas lack security.

The studies of urban perception evaluation present practical challenges. Traditional research methods, such as field surveys, neighborhood audits (Sampson and Raudenbush, 1999), and crowdsourced studies, are difficult to assess at large cross-city (Rundle et al., 2011), fine-grained, and uniform scales, while high survey costs and measurement errors are also drawbacks of these approaches.

Recent advances in digitalization technology have produced new means of data collection to provide high-resolution, real-time, and large-spatial-scale landscape image data support for urban perception studies. Publicly available street-view images (SVI), such as Google Street View, Mapillary (Neuhold et al., 2017), and Tencent Street View[1], are used to evaluate the urban perceptual quality of safety (Dubey et al., 2016), comfort (Liu et al., 2019), greenery (Li et al., 2015), vitality (Wei et al., 2022). With such massive image data collected on an international scale, some researchers applied deep/machine learning, the key techniques to exploit the value of these data. Deep/machine learning models extract features from SVI and further predict human perception. Most of the works are based on the MIT project *Place Pulse*

[a] https://orcid.org/0009-0006-4549-4851
[b] https://orcid.org/0000-0001-6930-3032
[c] https://orcid.org/0000-0003-4401-9267
[d] https://orcid.org/0000-0002-5728-9787
[e] https://orcid.org/0000-0001-5749-1590

[1] See https://map.qq.com (Accessed January 2023).

Li, X., Beaucamp, B., Tourre, V., Leduc, T. and Servières, M.
Evaluation of Urban Perception Using Only Image Segmentation Features.
DOI: 10.5220/0011969700003473
In *Proceedings of the 9th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2023)*, pages 200-207
ISBN: 978-989-758-649-1; ISSN: 2184-500X
Copyright © 2023 by SCITEPRESS – Science and Technology Publications, Lda. Under CC license (CC BY-NC-ND 4.0)

2.0 (PP2) (Dubey et al., 2016), which provides pairwise comparisons of Google SVI on six perceptual attributes, namely *safe*, *lively*, *beautiful*, *wealthy*, *boring*, and *depressing*.

However, the existing efforts largely depend on purely visual information (images) to train models. Some researchers have noticed the importance of semantic information of visual elements (e.g. car, traffic light, crosswalk) in images. People combine the scene they see with previous experiences to gain special feelings (Azma and Katanchi, 2017). The visual elements, a medium carrying the observer's previous experiences, can evoke different feelings in city observers' minds. For example, when people enter a new city, although no images of the place exist, they always have some experience of previously observed visual elements (e.g. traffic lights), which influence their perceptual activity (feeling safe). Thus, some studies introduced semantic segmentation techniques to assist urban perception prediction and explored how different visual elements impact human sensing (Ji et al., 2021; Zhang et al., 2018b; Zhang et al., 2018a; Xu et al., 2019). These works demonstrate that the semantic information of the visual elements can influence urban perception, although it is not the only factor that affects this process. The central question this paper asks is whether using only this non-visual and condensed information in deep/machine-learning-based urban perception prediction can lead to results comparable to traditional methods based on image analysis. Our work demonstrates and explains that applying only the semantic information extracted from different visual elements in SVI, can achieve acceptable performance for urban perceptual qualities prediction, with results close to those of image-based methods. Our main contributions are the following:

- A purely quantitative, non-image, and highly compressed derived dataset of PP2, in which we summarize each PP2 image as feature vectors that contain only semantic information.
- A neural network for urban perception evaluation paired with the derived dataset achieves an average accuracy of 62.4%.
- The effectiveness of the segmentation information is verified on classical machine learning models (Linear Regression, SVM, Random Forest, XGBoost) as well. The accuracy of models ranges from 60% to 62%.
- Our work shows that models using coarse semantic information instead of RGB images achieve acceptable results, despite the huge compression of information.

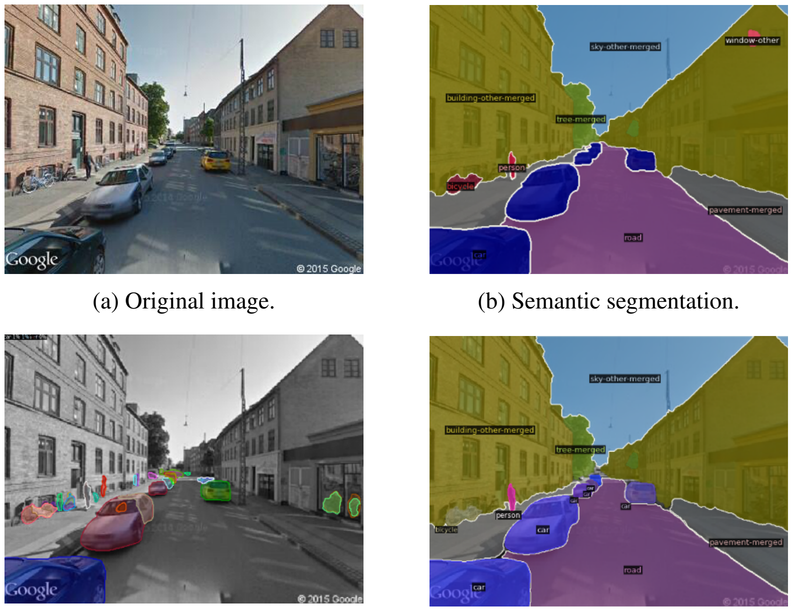
2 RELATED WORK

2.1 Place Pulse 2.0 Dataset for Urban Visual Perception

Place Pulse 2.0 (Dubey et al., 2016) is a specialized dataset for urban space perception at a global scale. It consists of 400×300 pixels images of 56 cities obtained from Google Street View, and 1,223,649 pairwise comparisons from the responses to six questions based on six perceptual attributes: *safe*, *lively*, *beautiful*, *wealthy*, *boring*, and *depressing*. For example, volunteers will be given a pair of street-view images and asked to answer questions, such as "Which place looks safer?", "Which place looks more depressing?".

2.2 Urban Visual Perception via Deep Learning

With PP2 such a massive geotagged image dataset, deep learning approaches enable the evaluation of human perception at a large scale. The classical deep learning models and their variants can be trained on PP2 and then predict the outcome of a pairwise SVI comparison. The pairwise comparison prediction task is often formulated as a binary classification task to give a prediction result of 0 or 1, representing one of the left or right images that performs better for the given criterion. The most classical RSS-CNN (Dubey et al., 2016) model employs VGGNet to extract image features and feeds them into the fusion and ranking sub-networks. It predicts pairwise comparison from two images while considering the ordinal ranking overall dataset, resulting in an average prediction accuracy of 68% on the six attributes. Subsequently, several researchers have developed this work and introduced variants of deep learning networks to improve prediction performance. Multi-task learning (Caruana, 1997), a new training paradigm that has been proven to improve the generalization of deep learning models, has been used to explore the relationship between different perceptual attributes and contribute to the improvement of prediction accuracy (Guan et al., 2021; Min et al., 2019). The widely popular attention mechanism (Vaswani et al., 2017) has also attracted the interest of researchers. Li et al. (Li et al., 2021) proposed that humans generate their cognition for street-view pictures from the key features rather than extracting all the information and making judgments. As an attempt to resemble this characteristic, the attention mechanism, which is regarded as a dynamic weight adjustment process based on features of the input image, is introduced (Min et al., 2019; Li



(a) Original image. (b) Semantic segmentation.

(c) Instance segmentation. (d) Panoptic segmentation.

Figure 1: A segmented PP2 image.

et al., 2022). The model (Li et al., 2022) with attention module reports a performance that exceeds the baseline slightly.

Not satisfied with just obtaining a comparative result, some researchers have tried to gain a deeper understanding of how human perception of the city is affected. The semantic information of visual elements in images has received attention, and the relationship between the visual elements and human perceptions has become a new topic worth exploring. The existing study approaches often contain a three-step process: first, extract the semantic information representation from SVI by image segmentation technique. The representation has different formats depending on their segmentation networks and the semantic information they contain. It is usually a structural vector in which each element indicates the information of an object category. Second, employ semantic information as a proxy for the urban environment to predict pairwise comparison outcomes. Third, the relationship of each visual element to perceptual attributes is quantified according to the model parameters. Xu et al. (Xu et al., 2019) extracted the distribution of 1,000 visual element categories through ImageNet 2012 classification network and added the output vector to the training network as an extra input to assist the visual perception prediction task. The experimental results prove that adding semantic information is beneficial, resulting in a 1.3% improvement in the overall accuracy of the original model with only image inputs. Zhang (Zhang et al., 2018b) and Ji (Ji et al., 2021) calculated the objects viewshed ratio, which represents the areal proportion of segmented objects, and used it to investigate the dependence between visual elements and human perceptual scores by adopting multiple linear regression. The above works show that semantic information can contribute to evaluating human perceptions of urban space and be a reference to help researchers understand the relationship between human perception and visual elements.

2.3 Panoptic Segmentation

Panoptic segmentation is a computer vision task that involves categorizing objects, as well as identifying and locating each instance of an object category. It can be seen as a combination of the typically distinct tasks semantic segmentation and instance segmentation (Kirillov et al., 2019). While semantic segmentation only focuses on assigning an object category label to each pixel in an image, and instance segmentation is aimed at detecting and distinguishing each instance of particular categories, panoptic segmentation goes one step further by combining these two approaches to provide a more detailed and accurate understanding of an image. For example, in Figure 1, the different cars are labeled as different *things* and are thus separate instances. The road is seen as *stuff* and is thus labeled as a single instance.

Masked-attention Mask Transformer (Mask2Former) (Cheng et al., 2022) is one of the state-of-the-art panoptic segmentation networks.

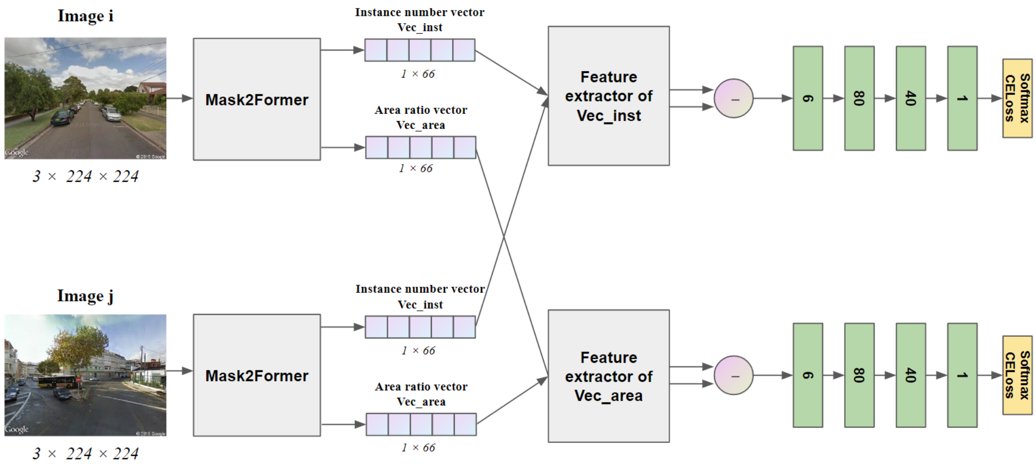


Figure 2: Architecture of proposed SS-NN.

Given an input image, the model is able to predict a category or instance label for each pixel. It has reached a panoptic quality score of 45.5 in classifying 66 object categories on Mapillary Vistas and has been employed in this study.

3 APPROACH

Unlike traditional urban perception methods that use only images as input for models' learning, we propose to take the semantic information extracted from panoptic segmentation scene as the only input to perform the urban scene analysis based on human perception. The process is decoupled into two steps: segmentation prediction and comparison prediction. First, we apply Mask2Former on PP2 images to obtain the panoptic segmentation results. Mask2Former was chosen because it outperforms a significant margin on Mapillary Vistas. The images are partitioned into multiple segments belonging to 66 categories: car, person, sky, road, void, etc. Then the statistics of the number of instances and pixels owned by each category in each image will be recorded as the segmentation result. Second, the segmentation result is fed into neural network models, which predict the results of pairwise comparisons on the six attributes. An overview of our network architecture is shown in Figure 2. In addition, we also test some classical machine learning models on only the attribute of safety using simplified inputs to explore the effectiveness of the semantic information on different models.

3.1 Segmentation Prediction

PP2 images go through a standard pre-processing pipeline used by the baseline network (Dubey et al., 2016), including rescaling, center cropping, and normalization. Subsequently, the pre-processed 224×224 pixels images are fed into the panoptic segmentation network Mask2Former, which has been trained on the Mapillary Vistas dataset, to parse each PP2 image and extract the feature vectors of urban physical appearance, shown in Figure 3. The feature vectors contain quantitative information about the number of instances and pixel areas possessed by each object category in the panoramic segmentation scene. We define index k as the $k-th$ of the 66 object categories in image I. In this way, the ϕ_{inst_k} represents the number of instances belonging to the $k-th$ category. Similar to (Ji et al., 2021; Zhang et al., 2018a), ϕ_{area_k} represents the areal proportion of $k-th$ category. Formally,

$$\phi_{area_k} = \frac{pixel_k}{pixel_I} \tag{1}$$

where $pixel_k$ is the number of pixels of $k-th$ category, $pixel_I$ is the total number of pixels of the image I. Consequently, for the image I, the area ratio vector Vec_{area} can be represented by a vector consisting of ϕ_{area} of all categories. Formally,

$$Vec_{area} = [\phi_{area_1}, \ldots, \phi_{area_{66}}] \tag{2}$$

Similarly, the instance number vector Vec_{inst} can be described as

$$Vec_{inst} = [\phi_{inst_1}, \ldots, \phi_{inst_{66}}] \tag{3}$$

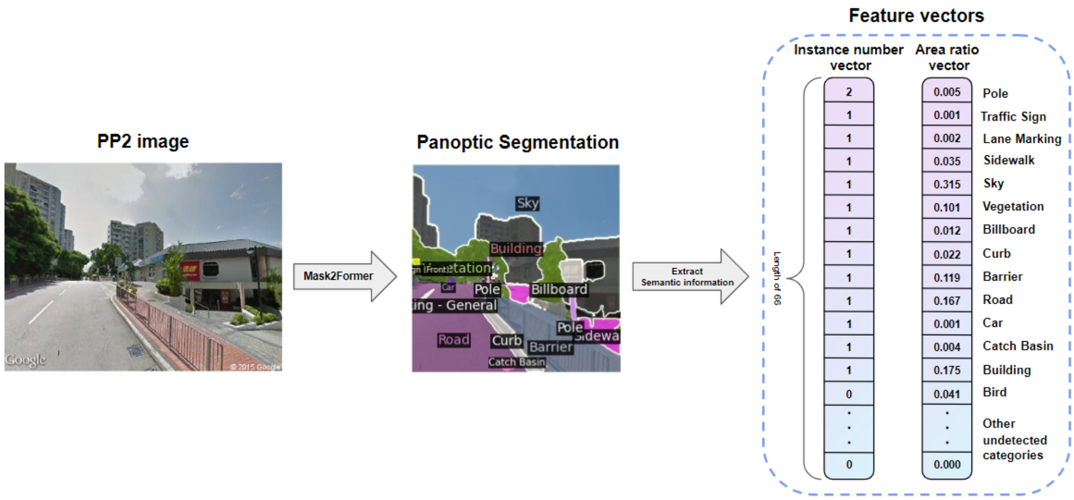


Figure 3: Extraction of the feature vectors. The PP2 image is fed into Mask2Former which outputs the panoptic segmentation image and semantic information of each category, including the number of instances and the area ratio. 14 of the 66 semantic categories are detected in this image. For the rest undetected categories, their number of instances and the area ratio are 0.

3.2 Comparison Prediction

We refer to Streetscore Convolutional Neural Network (Dubey et al., 2016) to create our Streetscore Neural Network (SS-NN), which can predict the winning image from a pair of images by using the feature vectors. For one image pair, the feature vectors of the left and right images first pass a feature extractor consisting of three linear layers, with a nonlinear relationship between the layers through the RELU function. The layers are composed of pairs of input and output sizes $(66,80),(80,40),(40,6)$. Applying the same feature extractor to both the left and right images aims at finding similar dimensionality-reduced features for the pair. Afterward, we make an elementwise difference between the obtained outputs, thus fusion the two outputs into one. The following learning network is also a three-linear layer structure with RELU function. The setting of layers is $(6,80),(80,40),(40,1)$. We train SS-NN for pair classification using the standard softmax with stochastic gradient descent. The softmax loss is specified as follows:

$$L_c = -\frac{1}{N}\sum_{n}^{N}\sum_{k}^{K}\mathbb{1}\{y=k\}log(g_k(Vec_i,Vec_j)) \tag{4}$$

where L_c is the loss, and N is the batch size. Vec_i, Vec_j denotes the feature vector extracted from the left and right images. $K=2$ means that there are two voting options, left and right. y is the label of each comparison. $\mathbb{1}$ takes 1 when y belongs to category k; otherwise takes 0. g is the softmax of final layer activation.

4 EXPERIMENTS

We evaluate our model performance using the PP2 dataset containing 1,343,004 pairwise comparisons (PC). The details of the dataset are shown in Table 1. Our SS-NN is trained with a batch size of 48 and an initial learning rate of 0.001. The code is available[2].

4.1 SS-NN Model

The performance of the SS-NN model is evaluated with a standard accuracy. The average prediction accuracy on the six attributes is shown in Table 2. For instance number vector and area ratio vector, the average accuracy reaches 60.2% and 62.4%, respectively. The performance of the SS-NN model with the feature vectors as input is slightly lower than the baseline RSS-CNN, which achieved an accuracy of 68%. In addition, compared to SS-CNN's 23,576,641 parameters, our SS-NN model has only 12,687 parameters. This lightweight model dramatically reduces the learning burden.

4.2 Machine Learning Models

Given the good performance of area ratio vectors on neural networks, we continue to explore their potential to be applied to different machine learning methods that are more stable and better interpreted. To further compress the data while retaining useful information, we selected only the top 14 object classes

[2] See https://github.com/LiXinyi9812/DLonPP2.git

Table 1: The percentage of PC belonging to six attributes of the total PC count (%).

	Safe	Lively	Beautiful	Wealthy	Boring	Depressing
PC ratio	32.82	23.75	14.11	11.15	9.25	8.92

Table 2: The accuracy of SS-NN using feature vector inputs (%).

	Safe	Lively	Beautiful	Wealthy	Boring	Depressing	**Avg.**
Instance number vector	59.6	62.3	59.8	59.7	62.0	57.6	**60.2**
Area ratio vector	61.9	62.4	62.9	62.0	62.0	63.0	**62.4**

with a high ratio of pixels over the whole dataset: *void*, *curb*, *fence*, *wall*, *road*, *sidewalk*, *bridge*, *building*, *lane marking - general*, *sky*, *terrain*, *vegetation*, *pole*, and *car*. The distribution of the ratio of the pixels is shown in Figure 4. For example, about 24% of the pixels in the dataset belong to the *road*. After this step, the amount of data in the area ratio vector has been reduced, and the feature vectors are standardized.

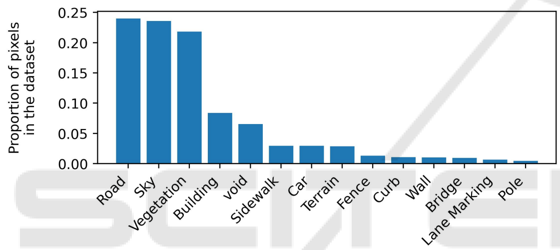


Figure 4: The distribution of the top-14 semantic categories in the dataset (98.4% of the pixels).

We choose the task "which image looks safer", and take the simplified area ratio vector as input to four popular machine learning models with good generalization ability: Linear Regression, Support Vector Machine (SVM), Random Forest, and eXtreme Gradient Boosting (XGBoost). The obtained prediction accuracy is shown in Table 3. All the machine learning models perform as well as the above deep learning model, resulting in an accuracy between 60% and 63%.

5 DISCUSSION

5.1 The Effectiveness of Feature Vectors

In this paper, we show that the feature vectors extracted from the panoptic segmentation scene achieve acceptable performance to predict the perception of urban space, compared to models with images as inputs. The feature vectors do not contain any spatial information and are highly compressed. Nevertheless, the obtained results are close to the ones obtained by larger models with images and convolutions. A possible explanation is that the feature vectors are fundamental components of some complex and valid metrics that impact urban perception, such as salient region saturation, visual entropy, green view index, and sky-openness index (Cheng et al., 2017). The prediction network simulates the computation of these complex urban perception metrics and combines them to give a comprehensive perception of the city. For instance, the area ratio of the vegetation category can be used to calculate the green view index related to aesthetics and living comfort, and the traffic light and building categories together reflect the imageability (Ma et al., 2021) in terms of the richness of space.

One noticeable result is that our SS-NN models have consistent performance across the six perceptual qualities, while the performance of the baseline model (Dubey et al., 2016) varies depending on the amount of data available for a given perceptual quality. The baseline gives a minimum of 62% for the depressing quality with the least amount of data, and a maximum of 73% for the safe quality with the largest amount of data. In contrast, our model performs almost identically in predicting the sense of depressing and safe qualities, despite a nearly fourfold difference in the amount of data. The range of the baseline's prediction accuracy is 9%, while the range of our model is 5% using instance number vector and 2% using area ratio vector. This indicates that our method is robust to variations in dataset size compared to the baseline. The possible benefit for urban perception studies could be that our model is able to obtain acceptable prediction results when introducing new perceptual qualities, even if a small amount of data is collected. This assumption might be demonstrated in future studies.

After being further compressed, the feature vectors reduced from 66 to the top-14 categories do not show a significant performance improvement or decline. The streamlined feature vectors still provide sufficient learning information and further reduce the learning burden of the models.

Table 3: The prediction accuracy of machine learning models on the safety attribute (%).

	Linear Regression	SVM	Random Forest	XGBoost
Area ratio vector	60.5	62.1	61.5	62.3

5.2 Experiment Limitations

The first step of this work is to extract 66 common categories of objects by Mask2Former. Nevertheless, the 66 categories are not comprehensive because they may not include all the objects that have an essential influence on the perception process, such as the visual elements *prisons* and *palaces* reported by (Xu et al., 2019).

5.3 Further Applications in Urban Planning

Predicting people's subjective perceptions of urban space by deep/machine learning models via transformed non-visual features offers a new method for urban planning. Our approach could help assess and guide city construction by providing valuable references and instructions for urban planners. Unlike most urban perception models, which are post-evaluation models and can only assess existing street-view images, our model can serve as an ex-ante evaluation model, allowing the use of simple non-visual numerical data to predict how residents will perceive the planned environment. For example, the number of instances of buildings, poles, and other objects, or the objects' estimated spatial occupation ratio in the urban planning scheme, can be converted to the proposed features vector as input to predict whether the planned space will bring a good sense to residents. In addition, as the foundation of automatic urban perception, street-view services face severe privacy violation accusations in some countries (Flores and Belongie, 2010), making it problematic to use the images of these areas as input to our models. Our proposed approach provides a way to circumvent this problem. The segmentation processing of street-view imagery automatically removes all visual components, making our approach free from privacy arguments and allowing future users to assess urban perception without any privacy concerns.

6 CONCLUSION AND FURTHER WORKS

This work shows that the non-visual semantic information extracted from urban landscape panoptic segmentation scenes could be solely used for urban perception. Our proposed segmentation feature vector allows deep/machine learning models to obtain acceptable results with less computational effort. To justify its effectiveness, we show the average prediction accuracy of our neural network and classical machine learning models, with results ranging from 60% to 62%. Compared to the baseline result of 68%, our results are acceptable. Further work should be done to verify that learning with semantic information can achieve a predictive performance comparable to image analysis methods. Some visualization techniques such as class activation map can be used in traditional image-input urban perception models, to locate the high-response regions that affect the prediction, and to explore whether there is a correspondence between the most influential image regions and the elements contained in our semantic feature vectors. Other future work will apply the machine learning models to assess the other five urban perceptual attributes by taking feature vectors as input. Besides, explore the relationship between the semantic categories and urban perception results to explain the validity of this novel data format. While the traditional methods that use deep convolutional neural networks with images as input have poor interpretability in urban perception tasks, the machine learning models such as Random Forests have better interpretability, allowing a clearer presentation of the relationship between the objects in images and the sense of urban space. Other valuable insights could also be learned by performing an in-depth comparison of the models' predictions to identify the shortcomings of the machine learning models with feature vectors compared to the deep learning models with images.

ACKNOWLEDGEMENTS

This work was funded by Centrale Nantes and RFI Atlanstic. We thank the Centrale Nantes Supercomputing Centre for providing the HPC resource throughout the project.

REFERENCES

Azma, S. and Katanchi, R. (2017). The effect of landscaping and building facades on perceptual-behavioral features of citizens. *Journal of History Culture and Art Research*, 6(3):264–281.

Caruana, R. (1997). Multitask learning. *Machine learning*, 28(1):41–75.

Cheng, B., Misra, I., Schwing, A. G., Kirillov, A., and Girdhar, R. (2022). Masked-attention mask transformer for universal image segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1290–1299.

Cheng, L., Chu, S., Zong, W., Li, S., Wu, J., and Li, M. (2017). Use of tencent street view imagery for visual perception of streets. *ISPRS International Journal of Geo-Information*, 6(9):265.

Cohen, D. A., Mason, K., Bedimo, A., Scribner, R., Basolo, V., and Farley, T. A. (2003). Neighborhood physical conditions and health. *American journal of public health*, 93(3):467–471.

Dubey, A., Naik, N., Parikh, D., Raskar, R., and Hidalgo, C. A. (2016). Deep learning the city: Quantifying urban perception at a global scale. In *European conference on computer vision*, pages 196–212. Springer.

Flores, A. and Belongie, S. (2010). Removing pedestrians from google street view images. In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition-Workshops*, pages 53–58. IEEE.

Guan, W., Chen, Z., Feng, F., Liu, W., and Nie, L. (2021). Urban perception: Sensing cities via a deep interactive multi-task learning framework. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 17(1s):1–20.

Ji, H., Qing, L., Han, L., Wang, Z., Cheng, Y., and Peng, Y. (2021). A new data-enabled intelligence framework for evaluating urban space perception. *ISPRS International Journal of Geo-Information*, 10(6):400.

Kelling, G. L., Wilson, J. Q., et al. (1982). Broken windows. *Atlantic monthly*, 249(3):29–38.

Kirillov, A., He, K., Girshick, R., Rother, C., and Dollar, P. (2019). Panoptic segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*.

Li, X., Zhang, C., Li, W., Ricard, R., Meng, Q., and Zhang, W. (2015). Assessing street-level urban greenery using google street view and a modified green view index. *Urban Forestry & Urban Greening*, 14(3):675–685.

Li, Y., Zhang, C., Wang, C., and Cheng, Z. (2021). Human perception evaluation system for urban streetscapes based on computer vision algorithms with attention mechanisms. *Transactions in GIS*.

Li, Z., Chen, Z., Zheng, W.-S., Oh, S., and Nguyen, K. (2022). Ar-cnn: an attention ranking network for learning urban perception. *Science China Information Sciences*, 65(1):1–11.

Liu, M., Han, L., Xiong, S., Qing, L., Ji, H., and Peng, Y. (2019). Large-scale street space quality evaluation based on deep learning over street view image. In *International Conference on Image and Graphics*, pages 690–701. Springer.

Ma, X., Ma, C., Wu, C., Xi, Y., Yang, R., Peng, N., Zhang, C., and Ren, F. (2021). Measuring human perceptions of streetscapes to better inform urban renewal: A perspective of scene semantic parsing. *Cities*, 110:103086.

Milam, A., Furr-Holden, C., and Leaf, P. (2010). Perceived school and neighborhood safety, neighborhood violence and academic achievement in urban school children. *The Urban Review*, 42(5):458–467.

Min, W., Mei, S., Liu, L., Wang, Y., and Jiang, S. (2019). Multi-task deep relative attribute learning for visual urban perception. *IEEE Transactions on Image Processing*, 29:657–669.

Miranda, A. S., Fan, Z., Duarte, F., and Ratti, C. (2021). Desirable streets: Using deviations in pedestrian trajectories to measure the value of the built environment. *Computers, Environment and Urban Systems*, 86:101563.

Neuhold, G., Ollmann, T., Bulò, S. R., and Kontschieder, P. (2017). The mapillary vistas dataset for semantic understanding of street scenes. In *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 5000–5009.

Rundle, A. G., Bader, M. D., Richards, C. A., Neckerman, K. M., and Teitler, J. O. (2011). Using google street view to audit neighborhood environments. *American journal of preventive medicine*, 40(1):94–100.

Sampson, R. J. and Raudenbush, S. W. (1999). Systematic social observation of public spaces: A new look at disorder in urban neighborhoods. *American journal of sociology*, 105(3):603–651.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, 30.

Wei, J., Yue, W., Li, M., and Gao, J. (2022). Mapping human perception of urban landscape from street-view images: A deep-learning approach. *International Journal of Applied Earth Observation and Geoinformation*, 112:102886.

Xu, Y., Yang, Q., Cui, C., Shi, C., Song, G., Han, X., and Yin, Y. (2019). Visual urban perception with deep semantic-aware network. In *International Conference on Multimedia Modeling*, pages 28–40. Springer.

Zhang, F., Hu, M., Che, W., Lin, H., and Fang, C. (2018a). Framework for virtual cognitive experiment in virtual geographic environments. *ISPRS International Journal of Geo-Information*, 7(1):36.

Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H. H., Lin, H., and Ratti, C. (2018b). Measuring human perceptions of a large-scale urban region using machine learning. *Landscape and Urban Planning*, 180:148–160.