ANALYSIS OF THE NEW ARCHITECTURAL DATASET *NEOFACADE* AND ITS POTENTIAL IN MACHINE LEARNING

ANALIZA NOWEGO ZBIORU DANYCH ARCHITEKTONICZNYCH *NEOFACADE* ORAZ JEGO POTENCJAŁU W UCZENIU MASZYNOWYM

NEOFACADE: AI APPLICATIONS

NEOFACADE: ZASTOSOWANIA W AI

Bianka Kowalska[1], Hubert Baran[2], Daniil Hardzetski[3], Halina Kwaśnicka[4], Aleksandra Marcinów[5], Małgorzata Biegańska[6]

[1] Studentka Wydziału Informatyki i Telekomunikacji, Politechnika Wrocławska,
Student of the Faculty of Information and Communication Technology, Wroclaw University of Science and Technology
e-mail: 252345@student.pwr.edu.pl
[2] Student Wydziału Informatyki i Telekomunikacji, Politechnika Wrocławska,
Student of the Faculty of Information and Communication Technology, Wroclaw University of Science and Technology
e-mail: 276938@student.pwr.edu.pl
[3] Student Wydziału Informatyki i Telekomunikacji, Politechnika Wrocławska,
Student of the Faculty of Information and Communication Technology, Wroclaw University of Science and Technology
e-mail: 252463@student.pwr.edu.pl
[4] Wydział Informatyki i Telekomunikacji, Politechnika Wrocławska,
Faculty of Information and Communication Technology, Wroclaw University of Science and Technology.
ORCID: 0000-0002-4368-4110, e-mail: halina.kwasnicka@pwr.edu.pl
[5] Wydział Architektury, Politechnika Wrocławska.
Faculty of Architecture, Wroclaw University of Science and Technology,
ORCID: 0000-0003-4409-3563, e-mail: aleksandra.marcinow@pwr.edu.pl
[6] Studentka Wydziału Architektury, Politechnika Wrocławska.
Student of the Faculty of Architecture, Wroclaw University of Science and Technology,
ORCID: 0009-0005-4302-2618, e-mail: 264659@student.pwr.edu.pl

1. Introduction

Architecture, as one of the oldest professions, has evolved over centuries, and with it the architectural design tools. In recent years, artificial intelligence (AI) has emerged in the field of architecture and revolutionized design optimization, empowering architects and designers. Traditionally, architecture is associated with creativity, aesthetics, and spatial design. However, in today's world, the scientific and technological aspects of design are also playing an increasingly important role. This is where artificial intelligence (AI) comes in, offering new tools and opportunities for architects. For instance, AI was implemented in the design of Bo-DAA apartment project in Seoul, South Korea. The project's requirements included the construction of multiple residential units and the provision of shared public spaces, including a communal workspace. The architect's use of a 3D model enabled the design concept to be created, which met all the requirements and moreover provided excellent lighting and views for each residential unit level [1]. For instance, the use of AI in the design of the Beijing Daxing International Airport has led to a more efficient and sustainable structure[7].

The mathematical foundations of artificial intelligence (AI), such as machine learning algorithms, neural networks, and vision systems, can be used in various areas of architecture. However, it's important to consider the ethical implications of AI in architecture. The true power of AI in architecture lies in its collaboration with human architects [2]. This interdisciplinary approach, combining the knowledge of architects with AI technologies, opens the way to innovative solutions and projects. It is a partnership that can contribute to improving the efficiency, functionality, and sustainability of architecture while making architects feel valued and integral to the process.

Artificial intelligence is not just a theoretical concept in architecture. It's a practical tool that can be used in project management and construction, helping plan and monitor work progress, optimize costs, and forecast possible problems. AI systems can analyze data related to the operation of buildings, predict their energy consumption, and respond to changes in environmental conditions in real-time, giving architects a sense of confidence and reassurance in their work. Using AI techniques, designers can generate and analyze thousands of design concepts, identify optimal solutions, or respond quickly to changing needs and requirements.

The share of artificial intelligence in architecture has been increasing since 2012 and is a topic of growing interest. The works published cover a wide range of applications, from performance-based studies to spatial programming and restoration works [2]. In recent years, generative artificial intelligence has made a notable surge within the realm of architecture, benefitting from the rapid growth of deep models, such as GANs (Generative Adversarial Networks) [1]. GANs consist of two networks: a generator, trained to produce outputs that cannot be distinguished from real images, and a discriminator, which is trained to detect the generator's fakes. Advanced generative models are capable of generating multiple design options in a short time, allowing architects to quickly explore different design concepts. AI

[7] see e.g., https://www.sensetime.com/en/case-detail?categoryId=32014

takes over the repetitive tasks, affording architects the opportunity to focus on the creative and strategic aspects of design.

One of the challenging design tasks is designing historical tenements facades, as it is not only required to place the façade in the tight proximity of other buildings, but also to meet the historical and cultural demands of the region. Artificial intelligence has also been employed in this context, with applications including the analysis of historical building data and the generation of design recommendations based on architectural styles that were popular in a specific era.

This paper aims to demonstrate the potential of the developed authors' dataset *NeoFacade* in some exemplary applications. The usefulness of this dataset is compared to two accessible benchmark datasets but from different cities and architectural styles.

The paper is structured as follows: section 2 briefly reviews the related work on the topic. The third section describes the datasets used in experiments, and the fourth section presents the results of various experiments. The summary concludes the paper.

2. Related work

Over the recent years, there has been a notable rise in the quantity of studies focusing on architectural design utilizing generative AI. Most of the work focuses on architectural plan design, which includes creating horizontal section views at specific site elevations, guided by objective conditions and subjective decisions. The authors [1] point out that more research needs to be done in the field of structural system design, architectural 3D form refinement and optimization design, and architectural facade design.

The applications of generative AI in structural system design primarily involve the prediction of structural layout and structural dimensions [1]. In the Bo-DAA apartment project described earlier, the architects utilized the 3D model and the architectural plan to define the building's spatial form and structural load distribution.

Façade design aims to create the building's external appearance. The requirements in this task include all structural design demands, as well as encapsulating the areas and positions of façade elements while adopting a specific style. Applications of generative AI in architectural façade design encompass two primary categories: generation of façade images, typically employing semantic segmentation maps of the facades, and the generation of semantic segmentation maps based on 2D images [1].

The generation approach utilizing semantic segmentation consequently involves generating images under geometrical constraints of the given area and can be posed as translating an input image into a corresponding output image. In 2018, Pix2Pix was introduced, an image-to-image translation method, capable of translating one possible representation of a scene into another using deep learning, given sufficient training data [3]. The framework employs Generative Adversarial Networks (GANs) in a conditional setting, meaning that not only is the generator tasked to fool the discriminator but also to be near the ground truth output. The authors explored the generality of conditional GANs by testing the method on various tasks, e.g., map to aerial photo, day to night, black and white to color and architectural labels to façade photo.

Segmentation task is a popular problem in computer vision. In semantic segmentation, we want to train a model that will assign a label for each pixel for a given image, contrary to classification, where we assign only one label to a whole image.

After the effective performance of Transformers architecture in natural language engineering tasks, interest in adapting Transformers for computer vision has risen. The first introduced model was a vision Transformer (ViT) created for classification tasks. ViT architecture was later used in segmentation transformer (SETR) architecture to study the performance of Transformers in semantic segmentation tasks. SETR performed well, and further work began to create a better architecture utilizing Transformers without SETR's limitations. One of those architectures is SegFormer [4]. Its main difference is using Mix Transformers (MiT), which returns multi-scale features, compared to ViT, which returns only one scale feature. SegFormer shows good accuracy and run-time on benchmark datasets.

Although neural network-based models are undeniably the most popular among artificial intelligence models these days, other approaches also find their applications in various architecture-related tasks. In the field of facades images generation, stochastic split grammars are used to build facade structure-aware generative models [5] A split grammar generates a facade image by splitting a given input shape into a set of smaller shapes, where each shape represents some part of a facade image. For instance, if the input shape is a rectangle representing a building, the split grammar might divide it into smaller rectangles representing the floors of the building. This process continues until the desired level of detail is reached and the final shapes are obtained, e.g., doors, windows, which are called terminals. In such a grammar, one may "merge" two shapes so that they are used interchangeably (with some probabilities) and obtain a stochastic grammar that can generate new facades examples. The approach may be extended to semantic segmentation masks.

3. Data used in experiments

Machine learning models require large amounts of high-quality training data to effectively learn complex patterns and relationships within it. The scarcity of structured architectural training data presents a significant challenge, undermining the initial stages of model training. Therefore, the *NeoFacade* dataset obtained in [6] serves as a crucial asset for the development of comprehensive and precise models.

NeoFacade represents a novel approach to addressing the growing demand for structured and high-quality data in the field of architecture. The dataset contains 394 annotated façade images of tenements in Wrocław. The images represent a variety of architectural styles from the 19th and 20th centuries. Each image is assigned a color-coded annotation mask, where the colors represent the various façade elements (e.g., windows, cornices, details). A detailed description of the dataset and its creation is available in [6].

As the efficacy of AI models is highly dependent on the quality of the data used for training, it is essential to conduct a comparative analysis to compare *NeoFacade* with existing benchmark datasets. Two available datasets of similar content and structure are the CMP Façade Dataset [7] and the Paris ArtDeco dataset [8]. The former consists of 378 rectified and cropped façade images from various locations. The pictures were manually annotated by the authors with a set of overlapping rectangular shapes, each coded to represent one of the 11 classes that were distinguished in the collection. The latter contains 79 façade images from Paris following the Art-deco style. Each picture is associated with an annotation text file containing a matrix of numbers in the image shape. Each number represents one of the 7 classes featured in the collection. Figure 1 illustrates example pictures and their annotations from both described datasets.

When compared with the two datasets, *NeoFacade* is distinguished by a greater number of images and their higher resolution, as shown in Table 1. The number of distinguished basic façade elements in the set is the same as in CMP, while Paris ArtDeco is characterised by the lowest number of classes.

Table 1. Comparison of facade datasets contents
Tabela 1. Porównanie zawartości zbiorów danych

Dataset	*NeoFacade*	CMP	Paris ArtDeco
No. of pictures	400	378	79
No. of classes	11	11	7
City	Wrocław	various	Paris
Mean resolution [MPx]	11,71	0,65	0,26
Imbalance ratio	2,62	2,61	1,11

The Paris Art Deco dataset exhibits the most balanced distribution of classes, with all distinguished elements occurring in almost all images. This is due to the distinguished elements being more common and the dataset not focusing on specific architectural details. In contrast, the other datasets display a less well-maintained balance of classes. CMP dataset and *NeoFacade* exhibit a comparable imbalance ratio.

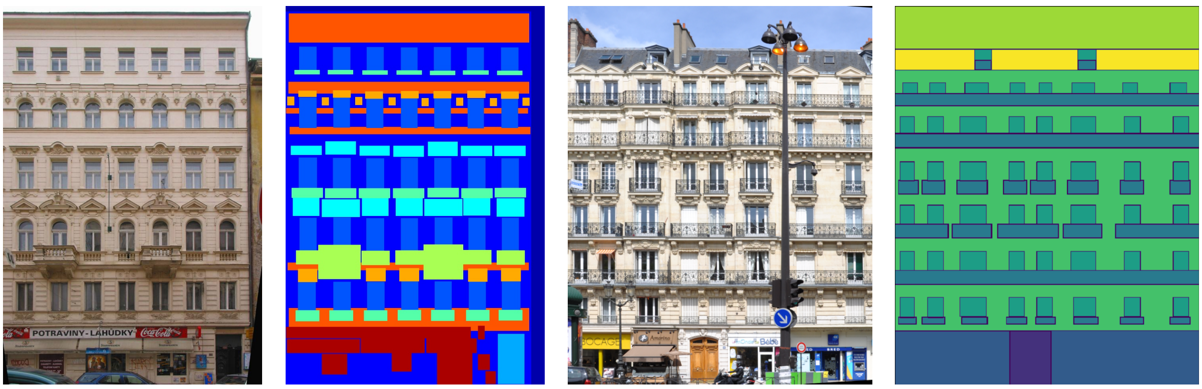

Figure 1. Example pictures and their annotations from the CMP dataset (left) and Paris ArtDeco (right)
Rys. 1. Przykładowe zdjęcia i ich adnotacje ze zbioru danych CMP (po lewej) i Paris ArtDeco (po prawej)

The exceptionally high resolution of images within *NeoFacade* allows us to generate exceptional quality images and conduct a detailed analysis of tenement facades from the 19th and 20th centuries. The dataset comparison provides a comprehensive analysis of multiple datasets within the architecture field, revealing differences in terms of size, scope and quality. The analysis confirms the value and potential impact of *NeoFacade* for driving future research advancements. The usefulness of the developed dataset was briefly studied, and the experiments are presented in the next section.

4. Short verification of potential of developed dataset in machine learning tasks

In the case of façade generation, the main tasks are segmentation and image translation. In this section we present the results of three machine learning models used for these tasks, which were trained and evaluated using the data described above.

4.1. Semantic segmentation

One of the popular tasks in vision systems is semantic segmentation. This process assigns a label to every pixel, allowing a detailed understanding of the image's contents. Several techniques have been developed for this task; they involve classifying each pixel in an image into a predefined category. Semantic segmentation is a powerful technique for detailed image analysis, enabling precise understanding and categorization of every part of an image.

We have trained the SegFormer model using a pre-existing implementation [9] with the three datasets described in Section 3 to evaluate how well-suited the datasets are for the semantic segmentation task. The objective of this experiment is to:

- compare the performance of the model trained on *NeoFacade* against those trained of existing benchmark datasets,
- identify the common problems encountered in façade semantic segmentation,
- identify the specific issues associated with training the model on *NeoFacade*.

Figure 2 and Figure 3 illustrate the segmentation results of models trained and evalauated with the three aforementioned datasets. Upon initial observation, the model demonstrates an ability to identify the majority of classes. The annotations produced by the model are placed correctly but do not maintain the original rectangular shapes.

Figure 2. Ground truth annotations and semantic segmentation results on CMP dataset (left) and Paris ArtDeco (right)
Rys. 2. Oryginalna anotacja i wyniki segmentacji semantycznej na zbiorze CMP (po lewej) i zbiorze Paris ArtDeco (po prawej)

Figure 3. Ground truth annotation and semantic segmentation results on NeoFacade dataset
Rys. 3. Oryginalna anotacja i wyniki segmentacji semantycznej na zbiorze NeoFacade

Error! Reference source not found. presents the metrics of the SegFormer trained on the three datasets. Notably, the results of the model trained on *NeoFacade* fall between the other two models. This can be attributed to the characteristics of the data. The Paris ArtDeco dataset, for instance, features fewer classes and clear facade images. In contrast, the CMP dataset often includes foreign objects in pictures, such as trees that heavily cover facades. To evaluate the quality of the performance of the trained model, we can use some metrics. The popular measures are:

- *Precision* – a ratio of correctly predicted positive observations to the total predicted positive observations.
- Recall – a ratio of correctly predicted positive observations to all observations in the considered class,
- F1 measure – a harmonic mean of recall and precision, it evenly takes into account precision and recall, is more suitable for comparing models.

Four measures obtained on three datasets are shown in Table 2.**Error! Reference source not found.** They are: (i) *MacroAvg* (macro average F1 measure), i.e., a measure F1 is calculated separately for each class and arithmetic mean value is calculated. It is unsuitable for imbalanced data because it prefers dominant classes. (ii) *Weighted Avg F1* (Weighted Average F1 measure), i.e., F1 calculated for each class separately is averaged with weights depending on the number of true labels of each class. The weight of class *x* depends on the proportion of data belonging to that class within the dataset. This measure considers the minor classes and is better for imbalanced data. A similar situation is with precision measurement – *Macro Avg Precision* and *Weighted Avg Precision*.

Regarding *NeoFacade*, the number of classes is comparable to that of the CMP dataset. However, unlike in CMP, the data is less obscured by foreign objects. Consequently, the weighted average of metrics is highly similar for *NeoFacade* and Paris ArtDeco datasets.

Table 3. SegFormer – performance measures for three data sets
SegFormer – miary skuteczności dla trzech zbiorów danych

Model	Macro Avg F1	Weighted Avg F1	Macro Avg Precision	Weighted Avg Precision
CMP	0.42	0.60	0.51	0.62
Paris ArtDeco	0.61	0.75	0.68	0.76
NeoFacade	0.50	0.73	0.54	0.75

To gain further insight into the models' performances, it is necessary to analyse the confusion matrix (**Error! Reference source not found.**). A confusion matrix is a matrix that provides an overview of the performance of a machine learning model on a set of test data. It is a tool for visualising and analysing the accuracy of a model's predictions and is frequently employed to assess the effectiveness of models which are designed to assign a categorical label to each data input.

The most prevalent error in the model trained on *NeoFacade* is mislabelling various classes as a wall, although this issue is also present in the two other models. This is attributed to the fact that the real labels are not pixel-level precise, and the model has an error in determining the shape of an object. The model does not correctly determine the contour of an element, but it still finds it in the correct spot.

A further limitation of the model is its tendency to mislabel other classes as the detail class. This occurs when the model mistakenly identifies other wall elements, such as window frames and cornices, as details due to their visual similarities. Of these mislabeled classes, balconies and roofs may appear the most surprising to occur. This can be attributed to the model's inability to comprehend these objects' volume accurately. In images, these elements appear flat and have a differing texture compared to the wall, which may lead to mislabeling.

The most challenging objects for our model are vertical elements. The model exhibited a complete inability to identify this label. Based on the analyzed examples containing the aforementioned class, we may assume the reason for such poor performance is that the elements in question closely resemble walls. The main distinct feature of the elements of the said class is their pillar shape, which our model failed to learn.

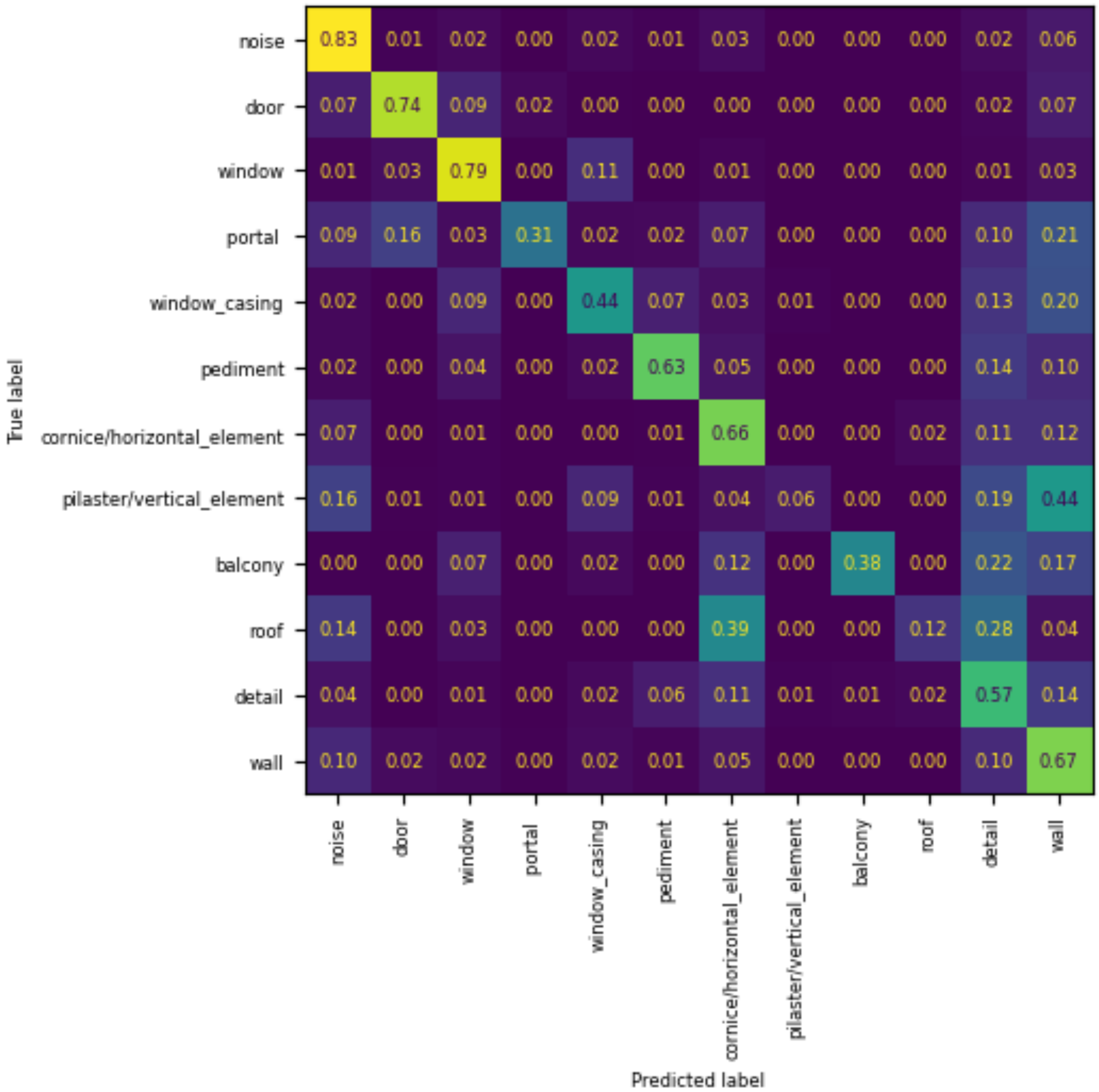

Figure 4. Confusion matrix - the performance of the model on NeoFacade
Rys. 4. Macierz pomyłek – działanie modelu na zbiorze NeoFacade

4.2. Image translation

Image-to-image translation is the process of transforming an input image into an output image while preserving some semantic properties. It encompasses a range of tasks, including image synthesis, resolution enhancement or image colorization. In the case of the *NeoFacade* dataset, image translation can be utilized to transform semantic segmentation masks to real façade images.

In the presented experiment, the ready-made implementation of the Pix2Pix model was used [3]. The model consists of two neural networks: a generator, whose task is to generate new images, and a discriminator, which classifies whether the generated image is real or fake. The generator learns the underlying connections between images from the two domains (segmentation masks and façade images), and the discriminator examines each fragment of the generated picture and attempts to classify the patch as authentic or artificial. The discriminator's examination of individual small fragments of the image facilitates the achievement of sharp and detailed results with the Pix2Pix model.

The model was trained for 250 epochs on two datasets separately: *NeoFacade* and CMP. Figure 5 and Figure 6 illustrate the example results of the Pix2Pix model on the segmentation mask to façade image translation task.

Figure 5. Results of the image2image translation task on NeoFacade images.
Rys. 5. Wynik zadania translacji image2image na obrazach ze zbioru NeoFacade.

Figure 6. Results of the image2image translation task on CMP dataset.
Rys. 7. Wynik zadania translacji image2image na obrazach ze zbioru CMP.

In both cases, the model was able to correctly generate desired façade elements in the relevant locations. However, more detailed objects, such as transoms and balconies, appear blurred in the generated images. It is the result of their less frequent occurrence in the datasets. The model encounters difficulties in filling the blank gaps left in the images that are present due to image warping.

4.3. Façade generation with grammars

We applied generative grammar for the facades generation, inspired by the approach from [5]. Several models have been trained on small subsets of the dataset. First, a rectangular lattice was generated for each facade example, using pixel labels from the segmentation mask. Lattices were built similarly to the one proposed by [10], with additional redundant split lines removal. Next, each facade lattice was converted into a hierarchical structure called a parse tree, which breaks down a facade into floors and then into smaller parts. Then, parse trees were converted into grammars and merged into one grammar, containing shapes from all facades in the training set. The merged grammar underwent symbols merging. The best symbols to merge were chosen by parsing candidate grammars from merging with 2D Earley Parser [11] and calculating their loglikelihood.

Figure 7. Facade generation with grammars using NeoFacade: generated facades on the left and similar real photos in the data set on the right.
Rys. 7. Generowanie fasad z zastosowaniem gramatyki dla zbioru NeoFacade: po lewej wygenerowane fasady, po prawej – najbardziej podobne zdjęcia ze zbioru danych.

In **Error! Reference source not found.**, the left column presents examples of generated facade images. The right column shows the examples from the training set the most similar to the ones generated. The model basically generates input examples with some small modifications (e.g., the image part of a window is replaced with another window's part, possibly from another input facade's image). The greater number of training steps could make induced grammars introduce more modifications to the input images.

5. Summary

The primary aim of this study was to present and analyze the innovative architectural dataset *NeoFacade*, highlighting its potential applications in machine learning. We demonstrated its quality and versatility by comparing this collection with two benchmark datasets of similar structure.

Our analysis included the evaluation of three different machine learning models: semantic segmentation, image translation, and image generation. Each model was tested using the dataset, and the results underscored the dataset's ability to produce satisfactory outcomes across these varied tasks. These findings suggest significant potential for further refinement and optimization in future studies.

The continuous expansion of the dataset, incorporating additional photographic material from diverse urban locations, is anticipated to enhance its applicability and performance. This ongoing enrichment is expected to yield increasingly favourable results, paving the way for developing an architect-friendly generative model capable of producing highly detailed and contextually accurate architectural designs.

Future research will focus on leveraging the detailed metadata included in the dataset. This metadata encompasses basic elements of facades and distinguishes between various architectural styles and elements. Such comprehensive annotations offer a rich source of information that can be employed to train more precise and sophisticated models. These models will be capable of generating facades that adhere to rigorous architectural and spatial specifications, thereby meeting the high standards required in professional architectural design.

Moreover, the planned inclusion of tenements from Berlin and Szczecin will further enhance the dataset's diversity and robustness. This expansion is expected to significantly improve the performance of the presented models, leading to better and more accurate results. The dataset will provide a more comprehensive foundation for training advanced machine learning models by incorporating these additional urban landscapes.

The *NeoFacade* dataset stands out as a high-quality resource for machine learning applications in architecture. Its rich and detailed annotations, combined with continuous updates and expansions, position it as a valuable tool for developing innovative solutions in architectural design. The findings of this study underscore the dataset's potential to support the creation of advanced, generative models that align with the precise demands of architectural practice.

6. References

[1] C. Li, *et al.*, “Generative AI for Architectural Design: A Literature Review,” Mar. 2024.

[2] B. Bölek, *et al.*, “A systematic review on artificial intelligence applications in architecture,” *Journal of Design for Resilience in Architecture and Planning*, vol. 4, no. 1, pp. 91–104, Apr. 2023, doi: 10.47818/DRArch.2023.v4i1085.

[3] P. Isola, *et al*. “Image-to-Image Translation with Conditional Adversarial Networks,” Nov. 2016.

[4] E. Xie, *et al*., “SegFormer: Simple and Efficient Design for Semantic Segmentation with Transformers,” May 2021.

[5] A. Martinovic, *et al*., “Bayesian Grammar Learning for Inverse Procedural Modeling.”. In CVPR Conference on Computer Vision and Pattern Recognition, 2013.

[6] A. Marcinów *et al*., “Building a Dataset of Wrocław’s Historic Tenements: Image Annotation for Machine Learning Applications,” Submited to *Architectus, WRUT Publishing House*, 2024.

[7] R. Tyleček and R. Šára, “Spatial Pattern Templates for Recognition of Objects with Regular Structure,” 2013, pp. 364–374. doi: 10.1007/978-3-642-40602-7_39.

[8] R. Gadde, *et al*., “Learning Grammars for Architecture-Specific Facade Parsing,” *Int J Comput Vis*, vol. 117, no. 3, pp. 290–316, May 2016, doi: 10.1007/s11263-016-0887-4.

[9] W. Yin, *et al*., “SSIW.” Accessed: Feb. 16, 2024. [Online]. Available: https://github.com/Xpitfire/SSIW/

[10] H. Riemenschneider *et al.*, “Irregular lattices for complex shape grammar facade parsing,” in *2012 IEEE Conference on Computer Vision and Pattern Recognition*, IEEE, Jun. 2012, pp. 1640–1647. doi: 10.1109/CVPR.2012.6247857.

[11] A. Martinovic, *et al*., “Early Parsing for 2D Stochastic Context Free Grammars”, Technical report KUL/ESAT/PSI/1301, KU Leuven, ESAT, Leuven, Belgium. 2013

7. Abstract

The share of artificial intelligence (AI) in architecture has been rapidly growing over the recent years. The collaboration between architects and AI developers has led to significant improvements in various design applications. Further development of machine learning techniques is highly dependent on the availability of large and structured datasets. The article aims to demonstrate the potential of a novel dataset containing annotated pictures of historical tenements, *NeoFacade*. Comparison of the dataset with existing benchmark datasets, the CMP Façade and the Paris ArtDeco datasets, highlights its exceptional features. Its applications in three machine learning tasks are also presented: semantic segmentation, image translation and image generation. In all three tasks, the models trained with *NeoFacade* provide satisfactory results and indicate the great potential of this collection. The planned further development of the dataset will allow the training of more precise models that will be able to distinguish more elements and features of the facades and assist architects in the tenement design process.

Udział sztucznej inteligencji (SI) w architekturze gwałtownie wzrósł w ciągu ostatnich lat. Współpraca pomiędzy architektami i programistami SI doprowadziła do znacznych usprawnień w wielu dziedzinach projektowych. Dalszy rozwój technik maszynowego uczenia jest silnie zależny od dostępności dużych i ustrukturyzowanych zbiorów danych. Celem artykułu jest ukazanie potencjału nowego zbioru danych, zawierającego zaanotowane obrazy kamienic historycznych, *NeoFacade*. Porównanie zbioru z innymi ogólnodostępnymi zbiorami: *CMP Facade* oraz *Paris ArtDeco* podkreśla jego wyjątkową jakość. Zaprezentowane również zostało wykorzystanie zbioru w trzech zadaniach uczenia maszynowego: segmentacji semantycznej, translacji obrazów oraz generacji obrazów. We wszystkich trzech, modele wytrenowane na zbiorze *NeoFacade* dają satysfakcjonujące wyniki i wskazują na wysoki potencjał zbioru. Planowany dalszy rozwój zbioru pozwoli na wytrenowanie dokładniejszych modeli, które będą w stanie rozróżniać więcej elementów i cech fasad oraz wspomagać architektów w projektowaniu kamienic.

8. Key words

dataset, image processing, machine learning, architecture

zbiór danych, przetwarzanie obrazów, uczenie maszynowe, architektura