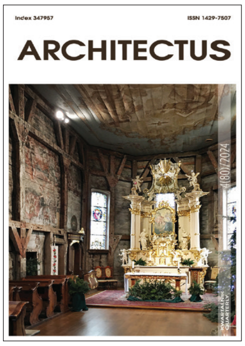

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Analysis of the new architectural dataset NeoFaçade and its potential in machine learning

Abstract

The presence of artificial intelligence (AI) in architecture has been growing rapidly in 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, structured datasets. The aim of the article is to demonstrate the potential of a novel dataset, *NeoFaçade*, which contains annotated pictures of historical tenements. A comparison of the dataset with existing benchmark datasets, the CMP Façade and the Paris Art-Deco 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 *NeoFaçade* 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 façades and assist architects in designing tenements.

Key words: dataset, image processing, machine learning, architecture

Introduction

Architecture, as one of the oldest professions, has evolved over centuries, and with it the tools of architectural design. In recent years, artificial intelligence (AI) has emerged in the field of architecture and has 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 AI comes in, offering new tools and opportunities for architects. For instance, AI was implemented in the design of the Bo-DAA apartment project in Seoul, South Korea (Rhee, Chung 2019).

Artificial intelligence, especially Machine Learning (ML) algorithms, neural networks, and vision systems, can be used in various aspects of architecture. When applying AI techniques, one should consider the ethical implications of AI in architecture (Liang et al. 2024). The true power of AI in architecture lies in its collaboration with human architects (Bölek, Tutal, and Özbaşaran 2023). Combining the knowledge of architects with AI technologies opens the way to innovative solutions and projects. It can improve architecture's efficiency, functionality, and sustainability,

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ensuring that architects feel valued and integral to the process (Nabizadeh, Nabizadeh 2023).

Artificial intelligence is 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 (Sourek 2024).

The presence of artificial intelligence in architecture has been increasing since 2012 and remains a topic of growing interest. Publications cover various applications, from performance-based studies to spatial programming and restoration work (Bölek, Tutal, and Özbaşaran 2023). 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 generative adversarial networks (GANs) (Li et al. 2024). 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 explore different design concepts quickly. AI takes over repetitive tasks, allowing architects to focus on the design's creative and strategic aspects.

One of the challenging design tasks is designing historical tenement façades, since the façade must be placed in the tight proximity of other buildings as well as meet the historical and cultural demands of the region. AI has also been employed in this context, with applications including the analysis of historical building data and the generation of design recommendations based on popular architectural styles from a specific era (Enjellina, Beyan and Rossy 2023).

This paper demonstrates the potential of the authors' dataset, *NeoFaçade*, using some example applications. The usefulness of this dataset is compared to two accessible benchmark datasets, but from different cities and architectural styles. *NeoFaçade* was created by a team from Wrocław University of Science and Technology. It contains façades of Wrocław's buildings, mainly from the 19th century. The intention is to use this dataset and others to renovate existing tenement façades or to construct infills between old buildings. In the next stage, this dataset will be expanded with photos of tenement façades from Berlin and Szczecin, since the tenements in these cities are of a similar style. More information about the current version of *NeoFaçade* can be found in (Marcinów et al. 2024). It is worth mentioning that we plan to make this dataset available for research.

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.

Related work

In recent years, there has been a notable rise in the quantity of studies on architectural design that makes use of generative AI. Our perception of visual culture becomes more mechanic with time, which influences architecture. This problem is considered in (Yau et al. 2023), where the authors debunk the three ways of thinking about architectural form in order to "lay the foundational preconditions for a machine-learnable architecture." 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. Many authors point out that more research is needed in the fields of structural system design, architectural 3D form refinement and optimization design, and architectural façade design (Sourek 2024; Ploennigs, Berger 2023; Nabizadeh, Nabizadeh 2023; Li et al. 2024; Bölek, Tutal, and Özbaşaran 2023).

The applications of generative AI in structural system design primarily involve the prediction of structural layout and structural dimensions (Pizarro et al. 2021). In the Bo-DAA apartment project described above, the architects utilized a 3D model and architectural plan to define the building's spatial form and structural load distribution (Rhee, Chung 2019).

Façade design aims to create the building's external appearance and includes all structural design demands and encapsulates the areas and positions of façade elements while adopting a specific style. Applications of generative AI in architectural façade design encompass two primary categories: the generation of façade images, typically employing semantic segmentation maps of the façades, and the generation of semantic segmentation maps based on 2D images (Xie et al. 2021). Segmentation is a popular problem in computer vision. In semantic segmentation, we want to train a model that will assign a label to each pixel for a given image; this is in contrast to classification, where we assign only one label to a whole image (Peng et al. 2020). The generation approach utilizing semantic segmentation consequently involves generating images under the geometrical constraints of the given area. It can be posed as translating an input image into a corresponding output image. In 2018, Pix2Pix was introduced; this image-to-image translation method is capable of translating one possible representation of a scene into another using deep learning, given sufficient training data (Isola et al. 2017). The framework employs GANs in a conditional setting, meaning that the generator is tasked with not only fooling the discriminator, but also being near the ground truth output (Newton 2019; Gui et al. 2021). The authors explored the generality of conditional GANs by testing the method on various tasks, for example, map to aerial photo, day to night, black-and-white to color, and architectural labels to façade photo.

Following the successful deployment of the Transformers architecture in natural language processing tasks, there has been a growing interest in adapting Transformers for computer vision. The first 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 achieved promising results, and further work began to create a better architecture utilizing Transformers without SETR's limitations. One of those architectures is SegFormer (Xie et al. 2021). Its main difference is that it utilizes Mix Transformers (MiT), which return multi-scale features, while ViT returns only single-scale features. SegFormer shows good accuracy and run time on benchmark datasets.

Although models based on neural networks are undeniably the most popular artificial intelligence models these days, other approaches also have applications in various architecture-related tasks. In the field of façade image generation, stochastic split grammars are used to build façade structure-aware generative models (Riemenschneider et al. 2012; Martinovic, Van Gool 2013a; Gadde, Marlet and Paragios 2016). A split grammar generates a façade image by splitting a given input shape into a set of smaller shapes, where each shape represents some part of a façade image. For instance, if the input shape is a rectangle representing a building, the split grammar might divide it into smaller rectangles representing the stories of the building. This process continues until the desired level of detail is reached and the final shapes are obtained (e.g., doors or windows), which are called terminals. In such a grammar, one may "merge" two shapes to be used interchangeably (with some probabilities) and obtain a stochastic grammar that can generate new façade examples. The approach may be extended to generating semantic segmentation masks.

Data used in experiments

Machine learning models require large amounts of high-quality training data to learn complex patterns and relationships within them effectively. The scarcity of structured architectural training data presents a significant challenge, undermining the initial stages of model training. Therefore, the *NeoFaçade* dataset obtained by (Marcinów et al. 2024) is a crucial asset for developing comprehensive, precise models.

NeoFaçade represents a novel approach to addressing the growing demand for structured, high-quality data in the field of architecture. The dataset contains 400 annotated images of tenement façades 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, or details). A detailed description of the dataset and its creation is available in (Marcinów et al. 2024).

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 *NeoFaçade* with existing benchmark datasets. Two available datasets of similar content and structure are the Center for Machine Perception (CMP) Façade Dataset (Tyleček, Šára 2013) and the Paris ArtDeco Dataset (Gadde, Marlet, and Paragios 2016). These datasets were selected because of their shared theme and labels, with the images depicting residential buildings and sharing elements of interest, such as balconies or details. 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 12 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 seven classes featured in the collection. Figure 1 illustrates example pictures and their annotations from both datasets.

Compared to the other two datasets, *NeoFaçade* is distinguished by its larger set of images and their higher resolution, as shown in Table 1. The number of basic façade elements distinguished in the set is the same as in the CMP dataset, while Paris ArtDeco is characterized by the lowest number of classes.

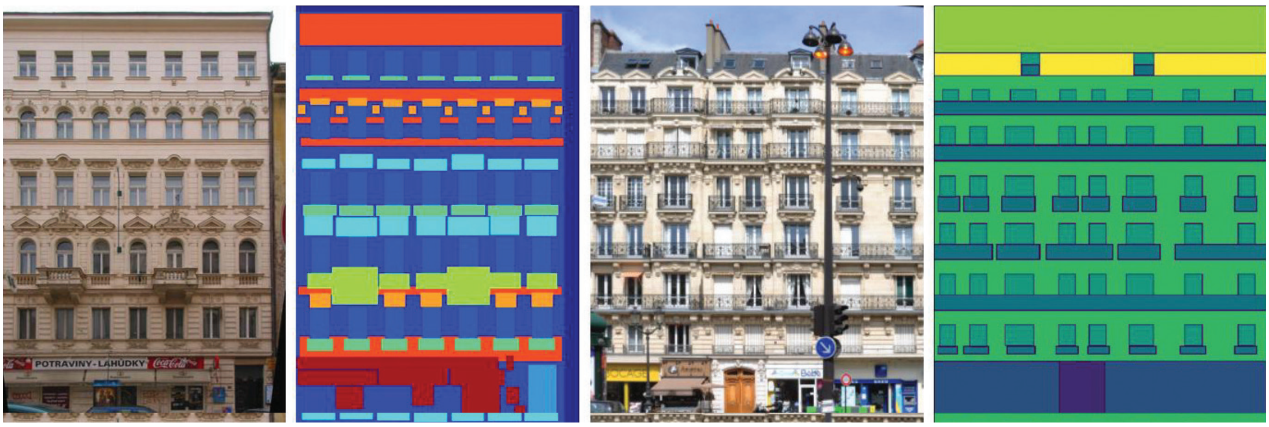

Fig. 1. Example pictures and their annotations from the CMP dataset (left) and Paris ArtDeco (right) (elaborated by B. Kowalska)

Il. 1. Przykładowe zdjęcia i ich adnotacje ze zbioru danych CMP (po lewej) i Paris ArtDeco (po prawej) (oprac. B. Kowalska)

Table 1. Comparison of façade datasets (elaborated by B. Kowalska)
Tabela 1. Porównanie zawartości zbiorów danych (oprac. B. Kowalska)

Dataset	*NeoFaçade*	CMP	Paris ArtDeco
Number of pictures	400	378	79
Number of classes	12	12	7
City	Wrocław	various	Paris
Mean resolution [MPx]	11.71	0.65	0.26
Imbalance ratio	2.62	2.61	1.11

The Paris ArtDeco dataset exhibits the most balanced distribution of classes, with all distinguished elements occurring in almost all images. This is due to its elements being more common and the dataset not focusing on specific architectural details. In contrast, the other datasets display less of a balance among classes. The CMP dataset and *NeoFaçade* exhibit a comparable imbalance ratio (the ratio of majority class to minority class).

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

Verification of the dataset's potential 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 ML models used for these tasks, which were trained and evaluated using the data described above.

Semantic segmentation

One of the popular tasks in computer vision systems is semantic segmentation. This process assigns a label to every pixel, providing 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 trained the SegFormer model using a pre-existing implementation (Yin et al. 2023) with the three datasets described in Section 3 in order to evaluate how well-suited the datasets are for semantic segmentation. The objective of this experiment was to:

– compare the performance of the model trained on *NeoFaçade* against those trained on existing benchmark datasets,

– identify the common problems encountered in façade semantic segmentation, and

– identify the specific issues associated with training the model on *NeoFaçade*.

Figures 2 and 3 illustrate the segmentation results of models trained and evaluated 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.

Table 2 presents the metrics of the SegFormer trained on the three datasets. Notably, the results of the model trained on *NeoFaçade* 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 façade images. In contrast, the CMP dataset often includes foreign objects in the pictures, such as trees that heavily cover the façades. We can use some metrics to evaluate the performance of the trained model. The popular ones are as follows:

– Precision – the ratio of correctly predicted positive observations to the total predicted positive observations.

– Recall – the ratio of correctly predicted positive observations to all observations in a given class.

– F1 measure – a harmonic mean of recall and precision which evenly takes into account precision and recall and is more suitable for comparing models.

Four measures obtained on three datasets are shown in Table 2. *MacroAvg* (macro-average F1 measure) is an F1 measure that is calculated separately for each class, then averaged using the arithmetic mean. It is unsuitable for imbalanced data because it prefers dominant classes. *Weighted Avg F1* (weighted average F1 measure) is an F1 measure calculated for each class separately and 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. The situation is similar with precision measurement: *Macro Avg Precision* and *Weighted Avg Precision*.

The number of classes in *NeoFaçade* 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 very similar for the *NeoFaçade* and Paris ArtDeco datasets.

To gain further insight into the model's performance, it is necessary to analyze the confusion matrix (Fig. 4). 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 visualizing and analyzing the accuracy of a model's predictions and is frequently employed to assess the effectiveness of models designed to assign a categorical label to each data input. The matrix compares predicted labels to true labels, which indicates the exact mistakes the model made. Instances where the prediction was accurate are represented on the diagonal of the matrix.

Fig. 2. Ground truth annotations and semantic segmentation results on the CMP dataset (left) and Paris ArtDeco (right) (elaborated by D. Hardzetski)

Il. 2. Oryginalna anotacja i wyniki segmentacji semantycznej na zbiorze CMP (po lewej) i zbiorze Paris ArtDeco (po prawej) (oprac. D. Hardzetski)

Fig. 3. Ground truth annotation and semantic segmentation results on the *NeoFaçade* dataset (elaborated by D. Hardzetski)

Il. 3. Oryginalna anotacja i wyniki segmentacji semantycznej na zbiorze *NeoFaçade* (oprac. D. Hardzetski)

Table 2. SegFormer – performance measures for three datasets (elaborated by D. Hardzetski)
Tabela 2. SegFormer – miary skuteczności dla trzech zbiorów danych (oprac. D. Hardzetski)

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
NeoFaçade	0.50	0.73	0.54	0.75

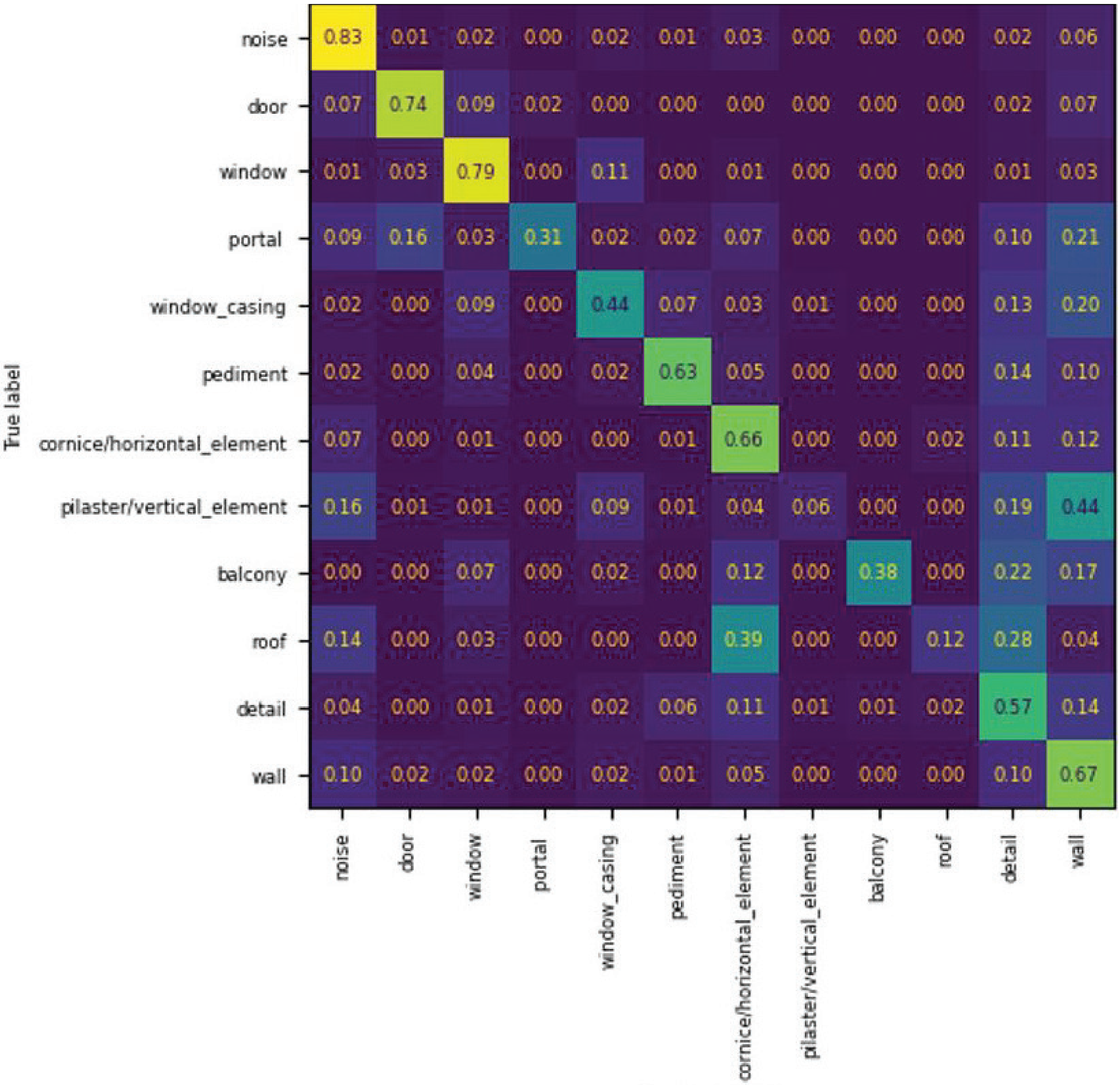

Fig. 4. Confusion matrix – performance of the model on *NeoFaçade* (elaborated by D. Hardzetski)

Il. 4. Macierz pomyłek – działanie modelu na zbiorze *NeoFaçade* (oprac. D. Hardzetski)

The most prevalent error in the model trained on *NeoFaçade* was various classes being mislabeled as a wall, although this issue was also present in the two other models. This is attributed to the fact that the real labels are not precise at pixel level 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. Balconies and roofs may be the most surprising of these mislabeled classes. This can be attributed to the model's inability to accurately comprehend these objects' volume. In images, these elements appear flat and have a different texture than 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 examples containing this class, we may assume the reason for such poor performance is that the elements in question closely resemble walls. The main distinct feature of vertical elements is their pillar shape, which our model failed to learn.

Image translation

Image-to-image translation is the process-s 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 *NeoFaçade* dataset, image translation can be utilized to transform semantic segmentation masks into real façade images.

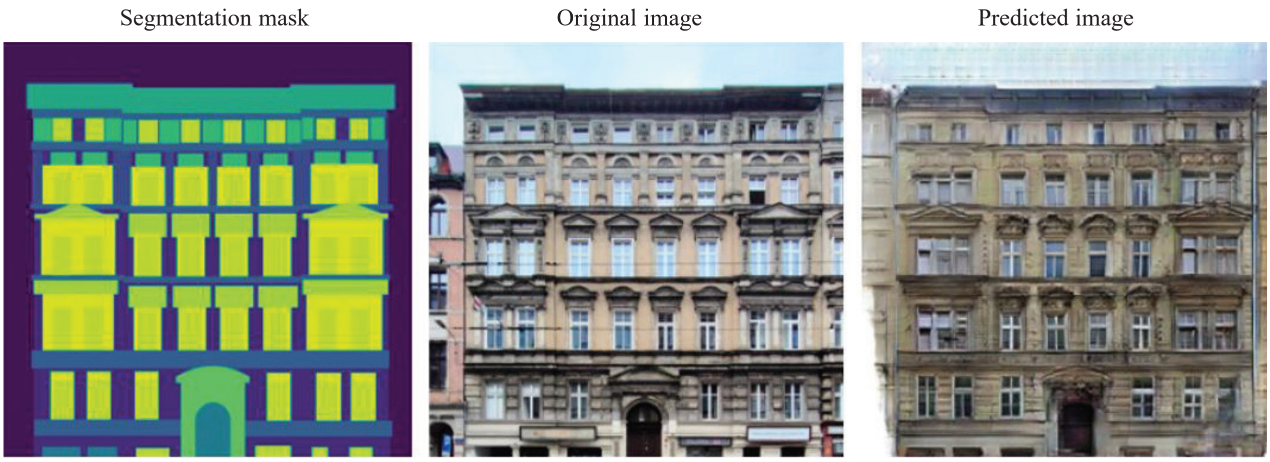

Fig. 5. Results of the image2image translation task on *NeoFaçade* images (elaborated by B. Kowalska)

Il. 5. Wynik zadania translacji image2image na obrazach ze zbioru *NeoFaçade* (oprac. B. Kowalska)

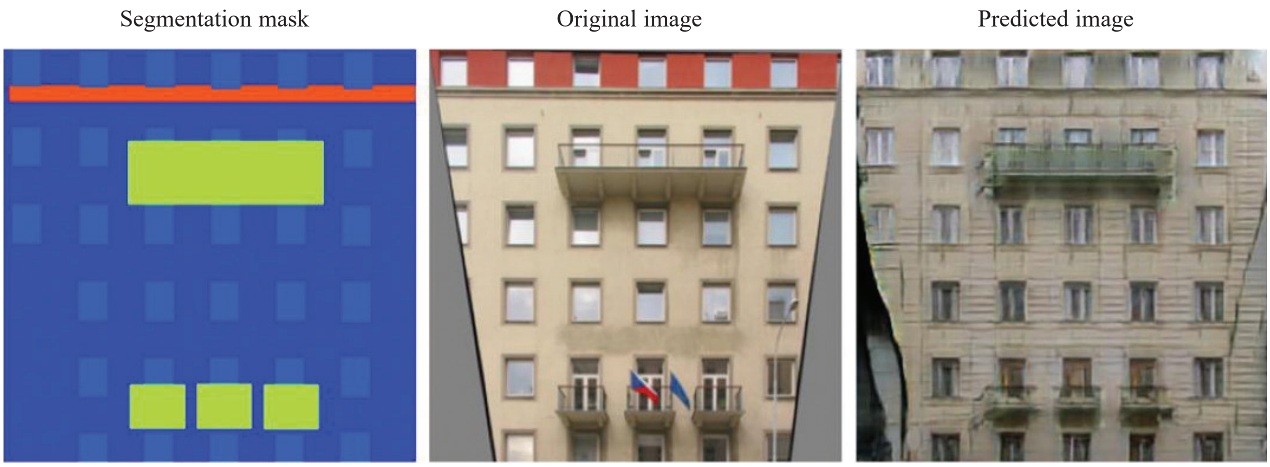

Fig. 6. Results of the image2image translation task on CMP dataset (elaborated by B. Kowalska)

Il. 6. Wynik zadania translacji image2image na obrazach ze zbioru CMP (oprac. B. Kowalska)

In the experiment, the ready-made implementation of the Pix2Pix model was used (Isola et al. 2017). 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 parts of the image facilitates sharp and detailed results with the Pix2Pix model.

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

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. This is because they occur less frequently in the datasets. The model encounters difficulties filling in the blank gaps left in the images due to image warping.

Façade generation with grammars

We applied generative grammar for façade generation, inspired by the approach from (Martinovic, Van Gool 2013a). Several models were trained on small subsets of the dataset. First, a rectangular lattice was generated for each façade example, using pixel labels from the segmentation mask. Lattices were built similarly to the one proposed by (Riemenschneider et al. 2012), with the additional removal of redundant split lines. Next, each façade lattice was converted into a hierarchical structure called a parse tree, which broke down a façade into floors and then into smaller parts.

Then, parse trees were converted into grammars and merged into one grammar, containing shapes from all façades in the training set. The merged grammar underwent symbol merging. The best symbols to merge were chosen by parsing candidate grammars from merging with 2D

Fig. 7. Façade generation with grammars using *NeoFaçade*: generated façades on the left and similar real photos in the data set on the right (elaborated by H. Baran)

Il. 7. Generowanie fasad z zastosowaniem gramatyki dla zbioru *NeoFaçade*: po lewej wygenerowane fasady, po prawej – najbardziej podobne zdjęcia ze zbioru danych (oprac. H. Baran)

Earley Parser (Martinovic, Van Gool 2013b) and calculating their log-likelihood.

In Figure 7, the left column presents examples of generated façade images. The right column shows examples from the training set that are the most similar to the generated ones. The model basically generates input examples with some small modifications (e.g., a window is replaced with another window, possibly from another input façade image). More training steps could make induced grammars introduce more modifications to the input images.

Summary

The primary aim of this study was to present and analyze the innovative architectural dataset *NeoFaçade*, 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 favorable 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 façades 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 more sophisticated models. These models will be capable of generating façades 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 *NeoFaçade* 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 highlight the dataset's potential to support the creation of advanced, generative models that align with the precise demands of architectural practice.

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Streszczenie

Analiza nowego zbioru danych architektonicznych NeoFaçade oraz jego potencjału w uczeniu maszynowym

Rola sztucznej inteligencji (AI) w architekturze gwałtownie wzrosła w ciągu ostatnich lat. Współpraca między architektami i programistami AI doprowadziła do usprawnień w wielu dziedzinach projektowych. Dalszy rozwój technik maszynowego uczenia w znacznym stopniu zależy od dostępności dużych i ustrukturyzowanych zbiorów danych. Celem autorów artykułu jest pokazanie potencjału nowego zbioru danych, nazwanego *NeoFaçade*, zawierającego opisane (anotowane) obrazy kamienic historycznych. Porównując zbiór z innymi ogólnodostępnymi zbiorami – *CMP Facade* oraz *Paris ArtDeco* – podkreślono jego potencjalną użyteczność. Zaprezentowane również zostało wykorzystanie zbioru w trzech zadaniach uczenia maszynowego: segmentacji semantycznej, translacji obrazów z generacji obrazów. We wszystkich trzech zadaniach modele wytrenowane na zbiorze *NeoFaçade* dają satysfakcjonujące wyniki i wskazują na wysoki potencjał zbioru. Planowany dalszy rozwój zbioru umożliwi wytrenowanie dokładniejszych modeli, które będą w stanie rozróżniać więcej elementów i cech fasad oraz wspomagać architektów w projektowaniu kamienic.

Słowa kluczowe: zbiór danych, przetwarzanie obrazów, uczenie maszynowe, architektura