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Understanding architecture age and style through deep learning

Maoran Sun, Fan Zhang *, Fabio Duarte, Carlo Ratti

Senseable City Lab, Massachusetts Institute of Technology, Cambridge, MA 02139, United States

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ABSTRACT

Architectural styles and their evolution are central to architecture history. However, traditional approaches to understand styles and their evolution require domain expertise, fieldwork and extensive manual processes. Recent research in deep learning and computer vision has highlighted the great potential in analyzing urban environments from images. In this paper, we propose a deep learning-based framework for understanding architectural styles and age epochs by deciphering building façades based on street-level imagery. The framework is composed of two stages: Deep 'Learning' the architecture and Deep 'Interpreting' the architecture age epochs and styles. In Deep 'Learning', a deep convolutional neural network (DCNN) model is designed to automatically learn about the age characteristics of building façades from street view images. In Deep 'Interpreting' stage, three components are proposed to understand the different perspectives regarding building ages and styles. In the experiment, a building age epoch dataset is compiled for the city of Amsterdam and Stockholm to understand the evolution of architectural element styles and the relationship between building ages and styles spatially and temporally. This research illustrates how publicly available data and deep learning could be used to trace the evolution of architectural styles in the spatial-temporal domain.

1. Introduction

Architectural styles evolve over time, complementing the development of social, economic and religious aspects of the society. Architectural styles and history are usually identified and studied by architects and architecture historians based on buildings' structure, material, decorations, form of architectural elements, as well as the contexts. Traditional studies often involve expertise around architectural styles, requiring field studies of representative buildings and extensive knowledge of the social and economic context. More importantly, the long time span and wide geographical distribution of global architectural styles and histories make it difficult to articulate the evolution of styles and genres on a large scale. The current study is limited by these time-consuming and knowledge-intensive methods.

Building age plays an important role in architectural history and styles, building energy modeling, real estate valuation, and urban planning. Previous literature has shown the connections building age has with other building stock attributes. Research shows that building age is a key factor in energy consumption modeling and an accurate estimation of building age would increase accuracies of building energy models and simulations (Aksoezen et al., 2015; Firth et al., 2010; Nouvel et al., 2017; Tooke et al., 2014). More accurate and completed building age data would help propose differentiated planning policies for successful renovation strategies. Building age estimation is also important in the classification of vulnerable properties for post-disaster recovery and earthquake simulation (Mangalathu et al., 2020; Steimen et al., 2004; Wieland et al., 2012). Successful identification of vulnerable buildings would benefit the decision-making for emergency responders and post-disaster recovery for local officials. Evidence shows that building age is influential on the valuation of real estate and rent prices (Brunauer et al., 2010; Zietz et al., 2008). Also, Dalmau et al. (2014) describe how building age data could be associated with urban planning and regulations.

Despite the importance in various fields, data of the construction period is often difficult to obtain. First of all, building age data is not always available. Biljecki and Sindram (2017) suggest that OpenStreetMap (OSM) contains very sparse data of building age in most cities. Even in some cities where it is open to the public, the coverage might not be enough for large-scale analysis. In the building stock dataset Agugiaro (2016) compiled for Vienna, compared to other building attributes (building class, building usage, etc.), building age has lower completeness. Secondly, it is labor-intensive and time-consuming to collect instance-level building age data in a large scale. Thirdly, while previous studies perform well in terms of prediction, limitations and

* Corresponding author.
E-mail address: zhangfan@link.cuhk.edu.hk (F. Zhang).

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challenges still exist in these methods. Most of the current studies involve data that are difficult to obtain or very complicated to process such as 3D GIS model and LiDAR. Multiple sources of data make it difficult to compile and calibrate so that human intervention and labor force are needed for this process.

With recent years development of deep learning, it has been proven that a machine is able to predict different aspects of built environments. A number of efforts have been devoted to predicting architecture ages with morphological descriptions of buildings (Biljecki & Sindram, 2017; Rosser et al., 2019; Tooke et al., 2014), classifying architectural styles (Doersch et al., 2012; Lee et al., 2015), and rating places to mimic people's perception (Naik et al., 2014; Zhang et al., 2018). Besides deep learning itself, using images to study built environments is getting more and more popular because of the increasing computation power. As the visual representation of buildings, street-level imagery has been widely used in a variety of fields in urban science. A number of research have adopted images to assess the built environment (Li et al., 2015), identify the unique objects in different cities (Zhang et al., 2019), and explore real estate valuation (Kang et al., 2021; Lindenthal & Johnson, 2021). We follow the trend of using street-level imagery to study built environments, not only because of its public availability but also because it is more intuitive than many other existing data. Fig. 1 shows street view images of buildings constructed in different ages. As human observers, we can roughly determine the order in which these buildings were built after some learning.

In this research, we apply deep learning not only to prediction and classification tasks, but also to building styles and history studies. With this approach, this paper aims to provide an alternative perspective for architectural research. A framework is implemented to demonstrate the potential of deep learning in understanding architectural styles. This framework consists of two stages: Deep 'Learning' the architecture and Deep 'Interpreting' the architecture ages and styles. In Deep 'Learning', a deep convolutional neural network (DCNN) model for building age epoch prediction is designed to learn about the characteristics of building façades in terms of building ages from street view images. In the Deep 'Interpreting' stage, three components are proposed to understand the four perspectives below regarding building ages and styles: 1) By applying the age epoch prediction model to different cities, we are able to understand the homogeneity of architectural styles across cities; 2) With analyzing what the model is paying attention to, visual clues about architectural element evolution is found; 3) The visualization of deep feature obtained from age epoch prediction model shows the relationship among architectural styles. 4) Lastly, the deep feature from age epoch prediction model, combined with an independent existing building style classification model is able to help trace the evolution of architectural styles.

As an implementation, a building age epoch dataset with more than 50,000 samples is created for Amsterdam, Netherlands. This dataset combines street view images with publicly available building age data from the Dutch city. Then, our designed DCNN model is trained with the dataset. Our results show the proposed components in the framework are effective in understanding the architectural history of Amsterdam, providing insights into detailed adoption and evolution of building styles in temporal and spatial domains.

The contribution of this work is twofold: First, we provide a scalable method to estimate building ages from public available data sources; Second, by analyzing and interpreting the results from the deep learning model, we develop an approach to trace the detailed evolution of building styles within the city. This demonstrates how artificial intelligence and data-driven approaches can be applied to facilitate the traditional research paradigm.

2. Related work

2.1. Building age epoch and style estimation

With the development of machine learning, considerable research over the last few years has been devoted to the estimation of building ages and architectural styles. For the style prediction task, most of the current research focuses on extracting low-level features or local image patches. Doersch et al. (2012) proposed detecting style-related patches associated with a specific city (i.e. Paris) from street view images. Patches are represented with Histograms of Oriented Gradients (HOG) and selected with an iterative linear SVM detector. Similarly, Lee et al. (2015) extract patches with Whitened HOG representation to estimate building age epochs and track the style evolution of building elements (e.g. windows, balconies, etc.). Unlike different previous approaches, Lindenthal and Johnson (2021) propose to extract deep features from pre-trained object detection models and build a simple multinomial classifier to predict architectural styles in Cambridge, UK. Besides architectural styles, researchers also apply deep learning on exploring styles and history of art (Elgammal et al., 2018). A style classification DCNN model was trained on 77K images of paintings. After training, an analysis of the model is conducted and shows that the final model is able to place artworks "in a smooth temporal arrangement mainly based on learning style labels." This research verifies the ability of deep learning to extract meaningful age-information from images of artworks.

For building age estimation task, many research chooses to extract morphological attributes from digital models including LiDAR data (Tooke et al., 2014), Digital Surface Model (DSM) (Rosser et al., 2019) and 3D GIS dataset (Biljecki & Sindram, 2017). Morphological attributes utilized in this research mainly are Area, Height, Number of Storeys and etc. Zeppelzauer et al. (2018) examine the use of photos for building age prediction. They first extract architecture-related patches. Patches are then fed into DCNN to classify the age periods of patches. A majority-voting rule over patch-level prediction results is established for building-level final decisions. Li et al. (2018) apply the combination of GSV and deep learning to building age estimation from images. They utilize a pre-trained model to extract built environment information from GSV with deep learning models. The extracted image features are then fed into Support Vector Regression model and predict the year of construction.

Despite these previous efforts to predict building ages and styles, there are still limitations. First, many of the research adopted low-level feature extraction to represent buildings. These efforts may achieve a certain level of performance, however, the approach they use does not

Fig. 1. GSV samples with buildings constructed in different periods (Image source: Google).

allow for a comprehensive, cognitive level understanding of the buildings. Second, LiDAR, 3D GIS model and DSM used in previous studies are not readily accessible and not available for many cities. Third, scalability remains challenging because of the complexity of the above data and the manual process required. Recent years of development on deep learning in computer vision and increasing coverage of street view services make street view images an ideal approach for building age and style estimation.

2.2. Application of street-level imagery in built-environment

In the field of architecture and urban planning, street view images, combining with deep learning have been used widely for understanding built environments. Utilizing such techniques, researchers investigate locational discriminative objects (Zhang et al., 2019; Zhou et al., 2014), measure perception of places (Naik et al., 2014; Zhang et al., 2018), and assess the built environment (Li et al., 2015). Besides, many research focuses on building-level analysis with GSV (Gonzalez et al., 2020; Yu et al., 2020). For example, Kang et al. (2018) combine the use of GSV and deep learning to classify the real use of buildings, including apartment, house, industrial, office, retail and other common land use.

Previous studies have demonstrated techniques, methods and practical applications of understanding built environments with images. Building on the above literature and following the trend of deep learning, our research combines DCNN model and street view images approach. This approach provides an accurate, automated and intuitive way to predict building ages in a large-scale urban area.

3. Data description

3.1. Study area

This work takes Amsterdam as the study site. As the capital city of the Netherlands, Amsterdam is characterized by its long history of urban development, dating back to the 12th century. After more than 700 years of expansion, it contains a mixture of architectural styles and buildings from different eras. Especially in the city center, the building years range from 1300 to 2020, which makes Amsterdam a challenging area for building age prediction. Besides the diversity of building styles and chronologies, the Netherlands maintains a relatively completed and open building stock dataset, including the geometry of buildings and various attributes related to the study. Access to these data offers possibilities for exploration. Fig. 2 shows the footprint of buildings in Amsterdam.

Besides Amsterdam, Stockholm is also selected for two reasons. First, we choose Stockholm to test the generalizability and transferability of our building age epoch prediction method. Second, more importantly, we look into what the model learns in Amsterdam and Stockholm to seek more knowledge regarding architectural styles and their evolution in different regions. The building age data of Stockholm is from real estate sales data obtained from Hemnet[1] and Booli,[2] two of the largest real estate marketplace companies in Sweden. The data covers transaction records from 2000 to 2020. The construction year of the properties is extracted from sales data and joined to building footprints from Open Stockholm.[3]

3.2. Building age data

Dutch municipalities record basic information about buildings and addresses as an openly available dataset named Basisregistraties Adressen en Gebouwen (BAG). It contains the construction year, current use, and registration status associated with each address in a building. BAG dataset is updated every month. This paper uses the data compiled in May 30th, 2020. We obtained preprocessed 3D BAG data (Ledoux et al., 2021; Stoter et al., 2020; Dukai et al., 2020, 2021) from the 3D geoinformation research group of the Delft University of Technology,[4] including 182,737 addresses in the Amsterdam metropolitan area. Each address is linked to a building footprint geometry and 173,863 of them contain a valid construction year. Table 1 shows the samples of building age data with an original year of construction, document date, geometry and unique identification number.

3.3. Building style data

Building styles data is used in this research mainly for exploring how building styles change with time. Building styles evolve with the change of building technology, aesthetics and ideology. While the transition between aesthetics and adoption of technology does not happen instantly. By comparing building ages with architectural styles, we are able to trace the actual evolution of styles.

The architectural style dataset, published by Lindenthal and Johnson (2021), is labeled by University of Cambridge into seven categories in chronological order. Details of style categories could be found in Table 2. In total, the dataset contains 29,177 samples and ranges from 17th century to the present. Though the building style data is from UK, it is still worth using in this study for several reasons. First, this study cares more about the temporal dimension of styles, instead of the exact styles associated with each building. Since Dutch and British architecture influenced each other historically (Louw, 2009; Arntz, 1953), they share many similarities in style and transition. Second, the style dataset achieves good performance and outputs reasonable results in Amsterdam, which will be discussed in detail in this paper.

3.4. Street view images

Street view images are virtual representations of the built environment and have been widely used as a proxy for real-world experiences and perceptions. Google Street View (GSV), as a feature of Google Maps, provides street view service that covers more than 100 countries over the world. Through Street View API, GSV could be retrieved at requested locations along with other parameters. The default view of street view images is facing along the street, which is not suitable for building instance-level classification tasks. Heading (the angle camera is pointing at) could be passed into the API as a parameter to customize the camera angle of images.

Here we present an algorithm to derive the heading parameter for retrieving building façade images from GSV. As shown in Fig. 3, we first project the midpoints of building façades calculated from BAG data onto the nearest street. With the projected points $S(x_s, y_s)$ and original façades midpoints $C(x_c, y_c)$, we are able to calculate the angle θ as shown in Eq. (1),

$$\theta = \begin{cases} arccos\left(\frac{V_n V_{sc}}{|V_n||V_{sc}|}\right), & \text{if } (x_c - x_s)\rangle 0. \\ 360 - arccos\left(\frac{V_n V_{sc}}{|V_n||V_{sc}|}\right), & \text{otherwise.} \end{cases} \quad (1)$$

where Vector V_n is the North Vector and Vector V_{sc} is the Vector from Point S to Point C.

$$V_n = (x_s, y_s + 1)$$

$$V_{sc} = (x_c - x_s, y_c - y_s)$$

As a result, GSV images are requested at the location of the projected

[1] https://www.hemnet.se/.
[2] https://www.booli.se/.
[3] https://dataportalen.stockholm.se/dataportalen/.
[4] https://docs.3dbag.nl/en/.

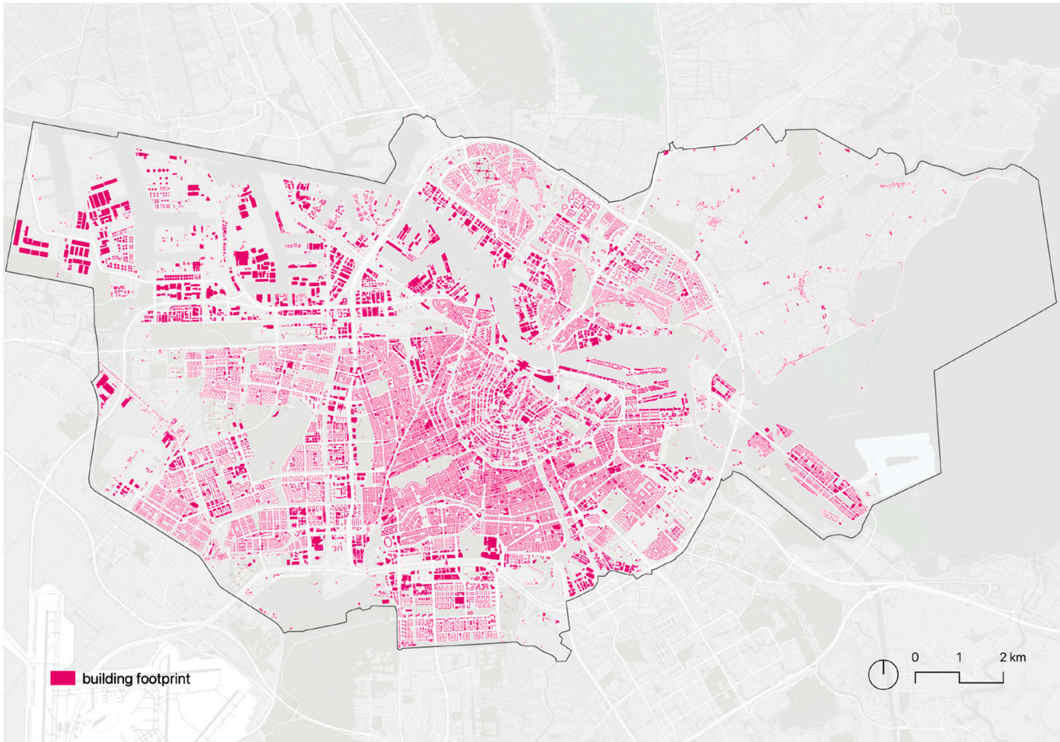

Fig. 2. Building footprints in the study area—Amsterdam.

Table 1
Building age data sample.

Document date	Original year of construction	Document number	Inspected	Geometry	Identification	Status
1993-05-28	1993	199300279	False	POLYGONZ ((95208.790440900.1900.000...	0014100010929791	Building in use
2006-11-07	1947	200603366	False	POLYGONZ ((99323.197442377.0640.000...	0014100010957694	Building in use
2019-06-24	2018	96128-2019:922920	False	POLYGONZ ((94219.531432967.4300.000...	0014100022192299	Construction started
2019-04-03	2019	43449-2019:945738	True	POLYGONZ ((91528.700441371.1900.000...	0014100040017850	Building in use

points with the specific angle θ.

3.5. Training dataset building

Though all GSV images are heading at the building façades, there are at least two types of samples that need to be removed: 1) the shooting point is far away resulting in a small building in the image; 2) buildings are occluded by trees or other objects. To do so, we proposed an evaluation method based on the quantitative representation of image content. The method follows three steps: 1) a candidate image is fed into a scene parsing DCNN model. Scene parsing models assign each pixel in an image a semantic category label (such as sky, building and tree). Here we employ a scene parsing model that is trained on the ADE20K dataset, which is a large-scale image dataset containing images labeled by 150 categories; 2) the ratios of each visual object of the image are calculated; 3) the images with the following two criteria are kept: 1) the percentage of building categories is the highest among all the category; 2) Buildings occupy more than 40 % of the image.

We treat the building age estimation as a classification task. Most buildings are constructed after 1900 in Amsterdam. It is worth having detailed age epochs before 1900 due to the fact that the city center has the majority of buildings built before 1900. Combining the architectural history and city development history, we adopt the following age periods: Early Stages (pre-1652), Eastern Expansion (1653–1705), French Influence Era (1706–1764), Southern Expansion (1765–1845), Neo Era (1846–1910), Interwar (1911–1943), Post-war (1944–1977) and Contemporary Era (1978–1994, 1995–2020).

After dividing the age epochs, the groups of pre-1652, 1653–1705 and 1706–1764 have much fewer samples than others. an imbalanced class dataset would lead to skewed predictive accuracy in the model (Japkowicz & Stephen, 2002). To solve this, data augmentation is performed for groups with fewer samples. Images are horizontally flipped and assigned with the original labels. For the groups with a larger number of samples, we randomly select data from them. As a result, a training dataset of 39, 211 samples is prepared for model training. The dataset is then split into two parts: 80 % is used for the modeling training process and the rest 20 % is used for evaluation purposes.

4. Framework

To demonstrate how deep learning could be leveraged in the study of architectural styles and history, we design a framework as shown in Fig. 4. First, we propose methods to deeply learn and understand instance-level building age epoch classification. Second, three types of

Table 2
Building style data attributes.

Style	Label	Era	Characteristics	Sample number
18th-century style	0	1714–1837	Sash windows, fan lights above doors, stucco on facades, wrought work grilles and railings	349
Early 19th-century style	1	1837–1870	Elaborate features such as carved barge boards or finials. Sash windows more affordable and wider	2150
Late 19th-century style	2	1870–1910	substantial bay windows, heterogeneous ornamentation, stained glass	4118
Interwar	3	1918–1939	Cost of building construction falls, distinctive two-pane windows	6737
Postwar	4	1950–1980	Embrace of high-rise as well as low-rise housing. Facades vary between brick, tiling, pebbledash and render	5473
Contemporary	5	1980–present	Innovative and distinctive building techniques	267
Revival	6		Contemporary buildings that emulate historic, mostly replica Victorian architecture	213

analysis are conducted to explore four aspects of architectural styles evolution through time. 1) Comparison across cities is conducted to test the homogeneity of building styles. 2) We perform salient feature mining with class activation map to explore architectural elements evolution. 3) Deep feature is extracted from building age epoch prediction model and visualized for exploring age-related information within images and understanding the relationship of styles. 4) A building style classification model is included and compared with deep feature to understand the changes of styles over age and the relationship between architecture ages and styles.

4.1. Deep 'Learning' the architecture with DCNN

With the dataset ready, we design a DCNN model for classifying building ages and architectural styles with street view images respectively. Though the method is applied to both tasks, this section will introduce the training process, evaluation of the results, and explorations on the trained model of building age epoch prediction task for clarity. It is worth noticing that the two models are independent of each other and only share the same methods during model training.

Our model is designed based on the backbone of Dense Convolutional Network (DenseNet121) (Huang et al., 2017). Four dense blocks are used in our network and each block is connected to every other block (Fig. 5). Compared to other architecture, our model is able to achieve higher accuracy with fewer parameters. The model is able to classify photos of building façades into 9 classes, namely pre-1652, 1653–1705, 1706–1764, 1765–1845, 1846–1910, 1911–1943, 1944–1977 and 1978–1994, 1995–2020.

We apply transfer learning from a model pre-trained on ImageNet dataset. The ImageNet dataset contains a wide range of common objects. The model pre-trained on this is able to understand objects and extract information from the images. Transfer learning allows us to fine-tune the base model and train the model to be more relevant to the task. More specifically, it updates the top layers of the neural networks, which are usually more specific to the training dataset. In general, transfer learning would lead to faster convergence, require less training data and lower the computational burden.

After training, the model is evaluated on the 20 % city-wide validation set. We adopt several methods to evaluate the result. The evaluation aims at exploring how well the model performs and the characteristic of misclassified samples. Firstly, we assess the classification accuracy with a confusion matrix that shows the recall, precision and F1 scores. Recall is defined as the number of true positives (TP) divided by the sum of true positives and the number of false negatives (FN) as shown in Eq. (2). Precision is the number of true positives over the sum of true positives and the number of false positives as shown in Eq. (3). F1-score is the harmonic mean of precision and recall as shown in Eq. (4).

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$F1 = 2^{*}\frac{Precision^{*}Recall}{Precision + Recall} \tag{4}$$

Secondly, we examine the spatial distribution of classification

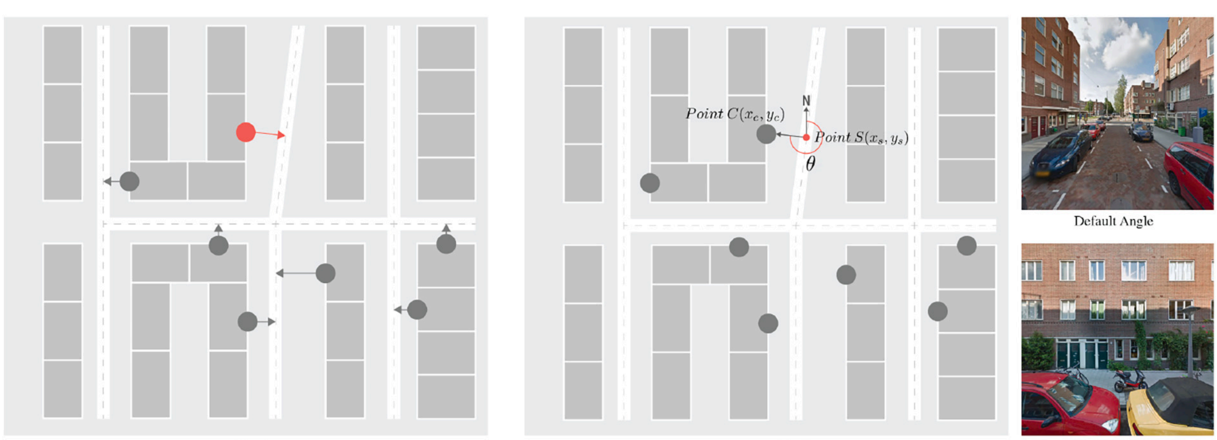

Fig. 3. Process for retrieving building façade from GSV. In step 1, midpoint of building façade (red point) is projected to nearest street, this point is used as location for requesting GSV, in step two, the angle between vector north and vector from request point to façade midpoint is calculated and fed into Google map API as angle of camera (Street view image source: Google). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

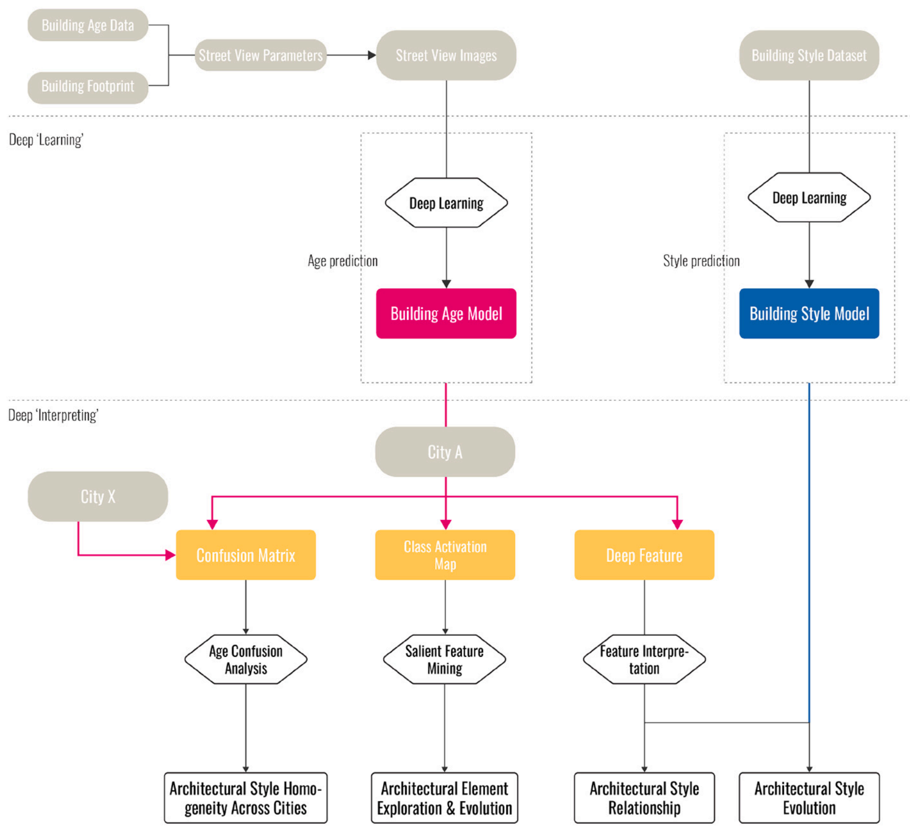

Fig. 4. Framework of understanding architecture ages and styles through deep learning. First, we propose methods for instance-level building age epoch classification to build a deep learning and understanding of architectural. Second, three types of analysis are conducted to explore four aspects of architecture ages and styles.

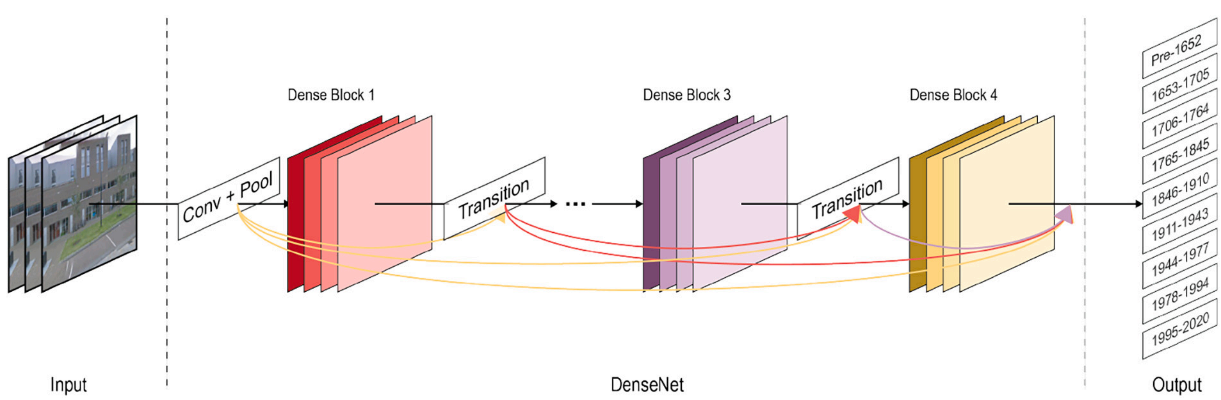

Fig. 5. Model architecture, the model takes GSV image as input and classifies photos of building façades into 9 classes. The network is designed based on the backbone of DenseNet121.

accuracy to see if any spatial pattern exists, as buildings within the same neighbourhood tend to be constructed during the same time. First, we plot the prediction error of each building in our dataset. We use C_{pred}–C_{gt} to represent the error, where C_{pred} and C_{gt} indicate the predicted class and ground truth class, respectively. Since the building age classes are labeled chronologically, this method not only shows if the model is predicting incorrectly, but also shows how incorrect the prediction is. Second, the classification results are spatially aggregated to 150-meter grids. Accuracy rate is calculated for each grid with correctly classified sample number divided by total sample number.

4.2. Deep 'Interpreting' the architecture age and style

4.2.1. What is the style homogeneity across cities?

The formation of architectural styles has always been a dynamic process and evolves across regions. Though they are influenced or twisted to accommodate the economical, social and religious backgrounds of different places, buildings of same styles from cities still share similarities in architectural elements, form and methods of construction. To understand the similarities of architecture in different cities, we propose an age epoch confusion analysis. More specifically, we apply the model trained on City A directly to City X. By comparing the detailed performance in different age groups, we are able to identify homogeneity in building styles across cities.

4.2.2. What does the model learn about architectural element styles?

Though our model makes classification in image-level labels, it is still worth exploring what elements within the images lead to the prediction so that future improvements could be made. Class activation map (CAM) is used to identify discriminative regions used by CNN to make predictions (Zhou et al., 2016). We add a global average pooling layer to the final convolutional layer of the original model. Then the weighted sum of outputs from the global average pooling layer is calculated as the final outputs. By looking at the CAM, we are able to understand which parts of images our model is paying the most attention and lead to the final classification. With CAM calculated for images, images are cropped with areas that draw the most attention. The cropped images are used for further explorations of building ages and styles.

4.2.3. What is the relationship among architectural styles?

Visualization of deep feature from samples is performed to show relationships among different building age groups. Generally, the deep feature extracted by the model from the images is able to represent the task-related information embedded within the images. In our case, the deep feature could be viewed as age-related information representation of each image. The original output deep feature of DenseNet model is 1024 dimensions. By adding two dimension reduction layers to the end of model, we obtain a 256-dimensional feature vector for each image. The feature vector was then projected into two dimensional plane with t-Distributed Stochastic Neighbor Embedding (t-SNE) (Van der Maaten & Hinton, 2008). The t-SNE assigns high-dimensional data a location in two-dimension space. Closer locations of data points represent similar characteristics of the original image. By doing so, we are able to inspect how the model understands building age information from images and the relationship of building styles.

4.2.4. What is the relationship between building age and style?

Architectural styles change over time and reflect a society's political, social and technical organization and are often associated with specific time periods. While the changes and adoptions of building styles are not instant, we would like to see if what model learns from building ages is able to reveal building style information as a way to explore the relationship between building ages and styles in Amsterdam through the eye of deep learning. With the model trained on building styles data, samples in building age dataset could be classified into 7 architectural styles as described by Lindenthal and Johnson (2021). This style classification is based on the visual characteristics of buildings and is an independent decision of age epoch predictions. By exploring the distribution of architectural styles within age groups, we are able to trace the transition between architectural styles.

5. Results

5.1. Model performance

5.1.1. Classification accuracy by class

The model and whole computation are implemented in Python and PyTorch on Ubuntu platform with two GeForce RTX 2080 Ti GPUs. Our model was evaluated on the 20 % city-wide validation dataset and achieved a total accuracy of **81.09 %**. Fig. 6 shows details about training samples and the training process. In addition to this, we compute a confusion matrix to explore how the model performs in each age epoch. Confusion matrix refers to a table comparing the prediction results made by the model and the ground truth. Table 3 presents the confusion matrix with actual number counted, normalized figures over the ground truth and recall, precision and F1-scores. The diagonal shows samples our model yields the same label as ground truth, while the off-diagonal space is where disagreement happens between prediction and actual label. Results show that our model achieves more than 80 % accuracies in most age epochs.

5.1.2. Classification accuracy by location

We also explore the spatial distribution of error at two scales. First, Fig. 7 shows the building instance-level model performance in the city center. Blue represents the old building being predicted as a new building, while pink indicates the model predicts new buildings as older ones. Grey means the prediction is correct. The map reveals that the majority of the errors are new buildings being predicted as old buildings. One potential reason for this is that, the canal area in the city center has been designated as UNESCO World Heritage and strict regulations for building renovation and reconstruction have been adopted here. Under the Dutch Monuments and Historic Buildings Act of 1988, the entire urban fabric and historic characteristics should be preserved here. New buildings are constructed in an old style and manner, which leads to these errors. Second, Fig. 8 shows the spatial distribution of aggregated classification accuracy. Classification results are aggregated to 150-meter grids and accuracy rate is calculated for each grid. As shown in the Fig. 8, the city center has a higher error rate than the outskirts. This might due to the high diversity of buildings ages, frequent renovations of old buildings in city center, and the strict regulations on renovated buildings stated above. Outskirts of Amsterdam present no evident spatial pattern, which indicates little spatial correlation on the classification results. We further calculate Moran's I (Moran, 1950) to quantitatively understand the spatial pattern. The Moran's I for results in outskirt of the city is 0.27. Moran's I has range from −1 to 1, with −1 being perfect dispersion, 0 representing perfect randomness and 1 meaning perfect clustering. The value of 0.27 here reveals that our predicted building age epoch in outskirts of Amsterdam shows weak spatial autocorrelation.

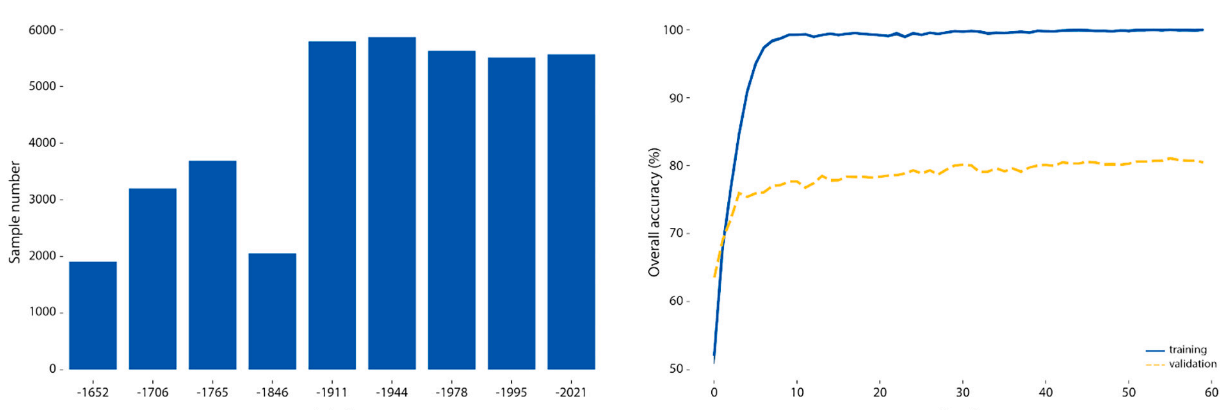

Fig. 6. Left. Sample numbers by class. Right. Learning curves during the training process.

Table 3
Confusion matrix for classification model trained on Amsterdam.

Ground truth	Prediction								
	-1652	-1706	-1765	-1846	-1911	-1944	-1978	-1995	-2020
-1652	**83 %**	4 %	4 %	1 %	3 %	1 %	1 %	3 %	1 %
-1706	1 %	**92 %**	4 %	1 %	1 %	0 %	0 %	1 %	0 %
-1765	1 %	5 %	**88 %**	2 %	1 %	1 %	0 %	1 %	1 %
-1846	1 %	6 %	6 %	**85 %**	0 %	0 %	0 %	1 %	1 %
-1911	1 %	2 %	3 %	1 %	**77 %**	7 %	1 %	5 %	2 %
-1944	1 %	1 %	1 %	0 %	5 %	**84 %**	3 %	3 %	2 %
-1978	1 %	1 %	1 %	0 %	2 %	6 %	**77 %**	7 %	5 %
-1995	1 %	2 %	2 %	1 %	5 %	3 %	6 %	**73 %**	7 %
-2020	1 %	1 %	1 %	0 %	3 %	4 %	4 %	6 %	**80 %**
Recall	0.83	0.92	0.88	0.85	0.77	0.84	0.77	0.73	0.8
Precision	0.82	0.8	0.81	0.86	0.82	0.81	0.85	0.74	0.81
F1-score	0.83	0.85	0.84	0.86	0.8	0.83	0.81	0.73	0.81

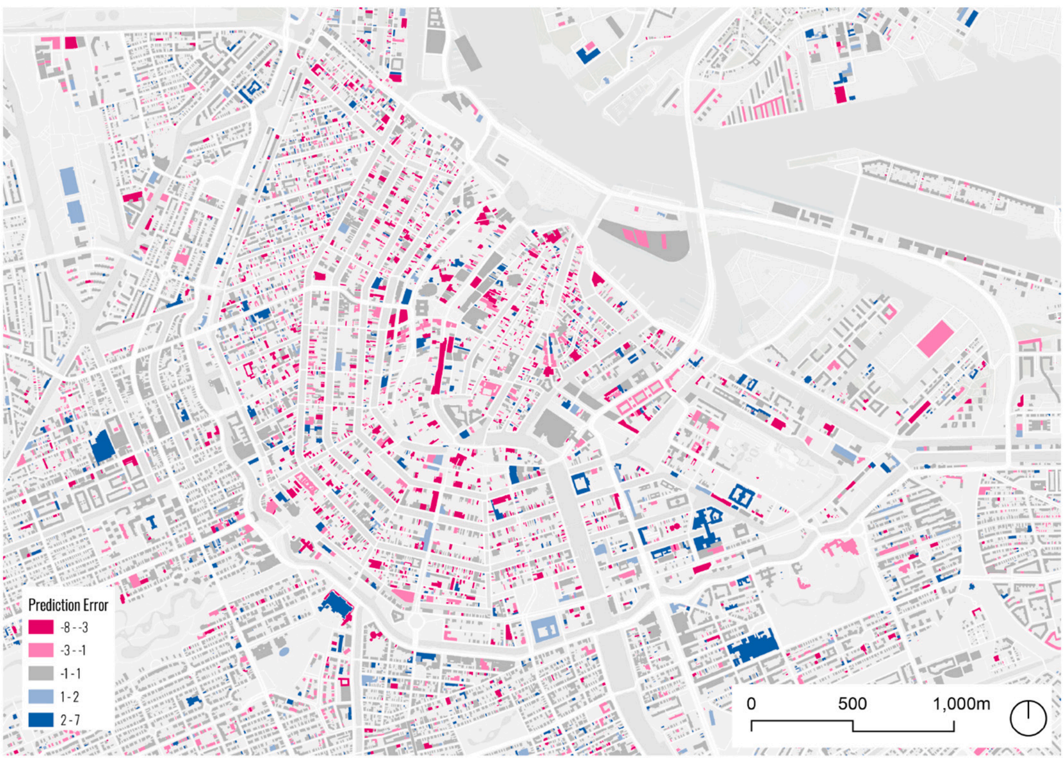

Fig. 7. Building instance level prediction performance. Pink represents new building being predicted as old building, blue means old building being predicted as new building. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.2. Deep 'Interpreting' the architecture age and style

5.2.1. What is the style homogeneity across cities?

To understand the architectural similarities across cities, we applied the model trained on Amsterdam building age dataset directly to Stockholm. The building age data is joined to building footprints from Open Stockholm. Then the same workflow is followed as described in Section 3.4 to retrieve GSV images for building façades. In total, 69,262 street view images are downloaded to be filtered further to make sure façades are clearly visible and not covered by other objects. As a result, 17,587 images labeled with years of construction are compiled as the building age dataset for Stockholm. For the total 17,587 samples, the overall accuracy is 24 %. As shown in Table 4, 56 % of Stockholm buildings constructed between 1706 and 1764 are predicted as 1846–1910, this indicates a temporal mismatch in building styles between the two cities. For the age periods of 1978–1994 and 1995–2020, the model achieves accuracies of 42 % and 45 %. This reveals similar building forms and styles between the two cities during these periods.

Besides exploring the style homogeneity across cities, we extend our building age epoch prediction methods to Stockholm to evaluate the generalizability of the framework. We fine-tune the pre-trained model from Amsterdam with building age epoch data from Stockholm. With 17,587 samples in total, 2587 samples are held for evaluation and 15,000 are used for training. Ten training sets with different sample sizes, from 1500 to 15,000 by increments of 1500, are used in this test to examine the minimal samples needed for transferring. Fig. 9 illustrates the overall accuracy achieved by different training sets. With 1500 samples from Stockholm, our methods could correctly classify the building ages of 57 % of images from the evaluation set. With all 15,000 samples used for training, the model is able to achieve a total accuracy of 72 %. This experiment verifies the generalizability of our building age epoch prediction method. It shows that with few ground truth samples from the new city, our method could achieve relatively high accuracy in new cities.

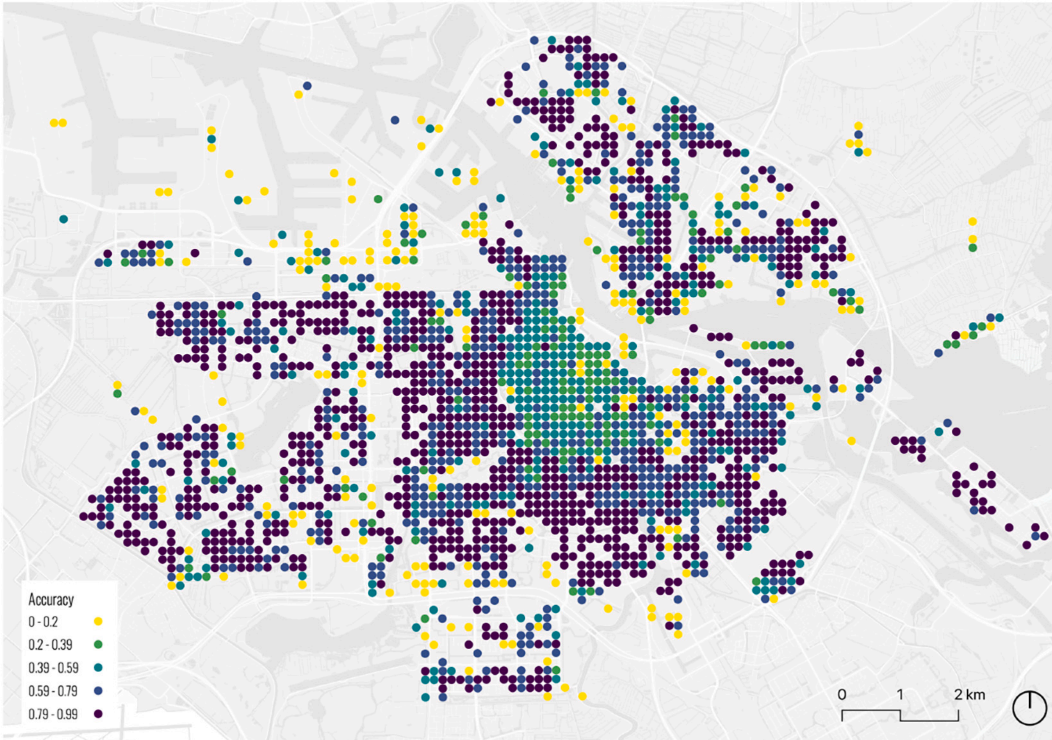

Fig. 8. Building age epoch prediction – accuracy measured at 150 m grid level.

Table 4
Confusion matrix for classification with applying model from Amsterdam to Stockholm.

Ground truth	Prediction								
	-1652	-1706	-1765	-1846	-1911	-1944	-1978	-1995	-2020
-1652	11 %	1 %	0 %	1 %	44 %	1 %	2 %	11 %	28 %
-1706	33 %	0 %	0 %	0 %	17 %	0 %	0 %	33 %	17 %
-1765	0 %	3 %	6 %	3 %	56 %	3 %	6 %	17 %	8 %
-1846	7 %	3 %	0 %	3 %	23 %	3 %	0 %	43 %	17 %
-1911	1 %	4 %	1 %	6 %	33 %	7 %	6 %	17 %	25 %
-1944	0 %	1 %	1 %	1 %	9 %	15 %	14 %	37 %	22 %
-1978	0 %	0 %	0 %	1 %	4 %	8 %	25 %	36 %	26 %
-1995	0 %	0 %	1 %	1 %	4 %	10 %	11 %	42 %	32 %
-2020	0 %	0 %	0 %	1 %	3 %	3 %	13 %	34 %	45 %

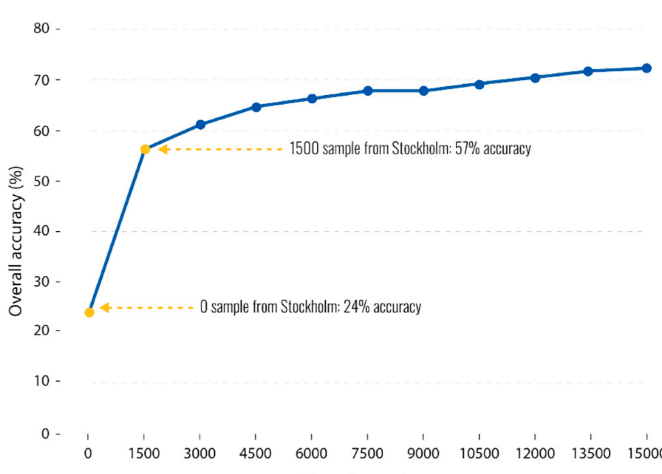

Fig. 9. Accuracy changes as sample number increases, with few samples (1500) ground truth from Stockholm, the accuracy is able to achieve 57 %.

5.2.2. What does the model learn about architectural element styles?

To explore how the model makes decisions and trace the evolution of architectural elements, CAM is adopted to validate samples of the dataset. Fig. 10 indicates clear patterns of CAM results with semantic objects being highlighted rather than random parts of the buildings. Also, it shows that the informative image regions mostly cover the windows or doors. What's more, the model always focuses on the second floor or intersection of the first and second floor. As the first floor of buildings are often renovated or transformed for retail purpose, Lee et al. (2015) crop the first floor from façades. Our model shows that no such pre-processing is needed in our workflow as it pays little attention to the first floors. Similarly, cars, bikes and pedestrians in the front of street view images are usually ignored as they are not related to building ages. Essentially, the model learns the efficient features from the images, and ignores the irrelevant information in the images automatically.

Lee et al. (2015) trace how architectural elements evolved in Paris over the 200-year span. Similarly, we crop the original images and keep only the discriminative regions based on CAM. According to the cropped images, our model pays more attention to windows than other objects when making decisions. Fig. 10 illustrates how windows are associated with building ages as a hint for window style evolution. Windows in

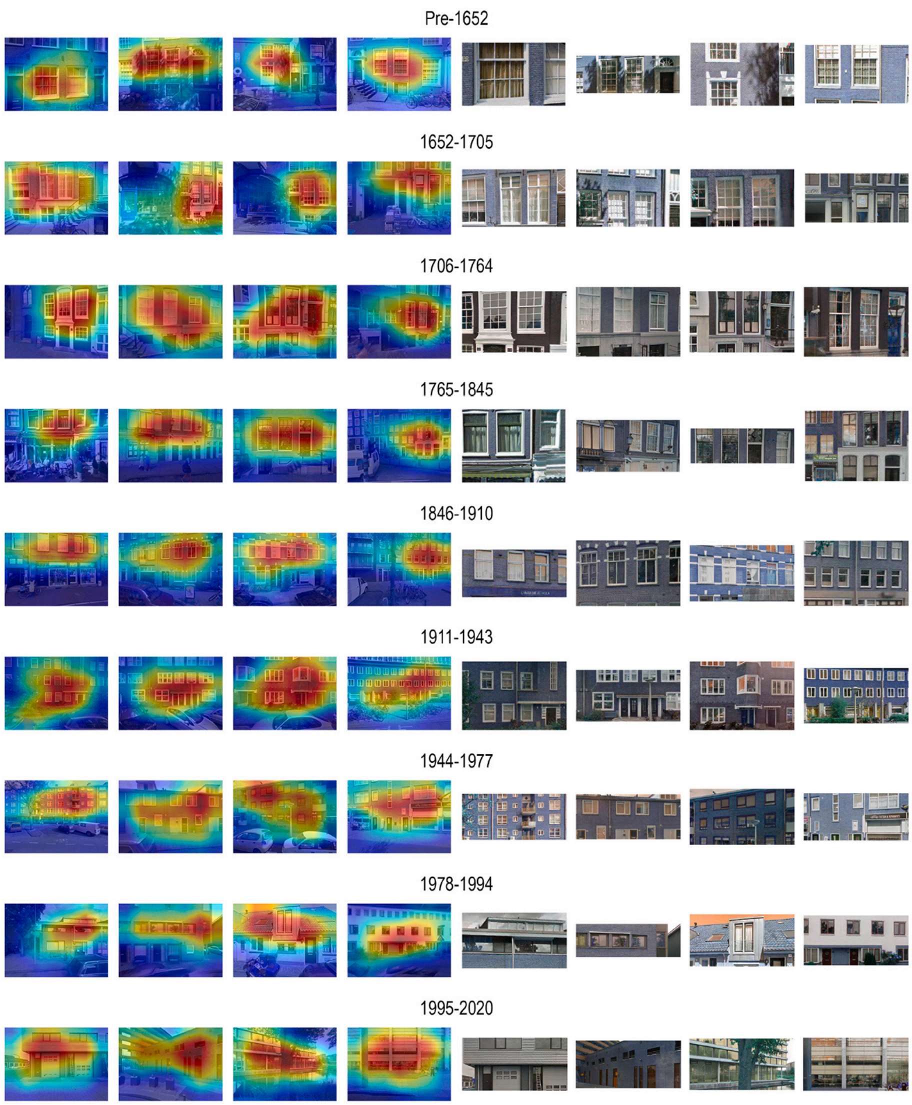

Fig. 10. Left: CAM overlayed on original images. The informative image regions (red areas) mostly cover the windows or doors between first and second floors. Right: Image cropped according to CAM shows the evolution of windows. Windows in early eras usually contains wider frame, more decorations and are narrower. Recent window styles are featured with square and horizontal shape with thinner frame, less decoration and less depth (Building façades image source: Google). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

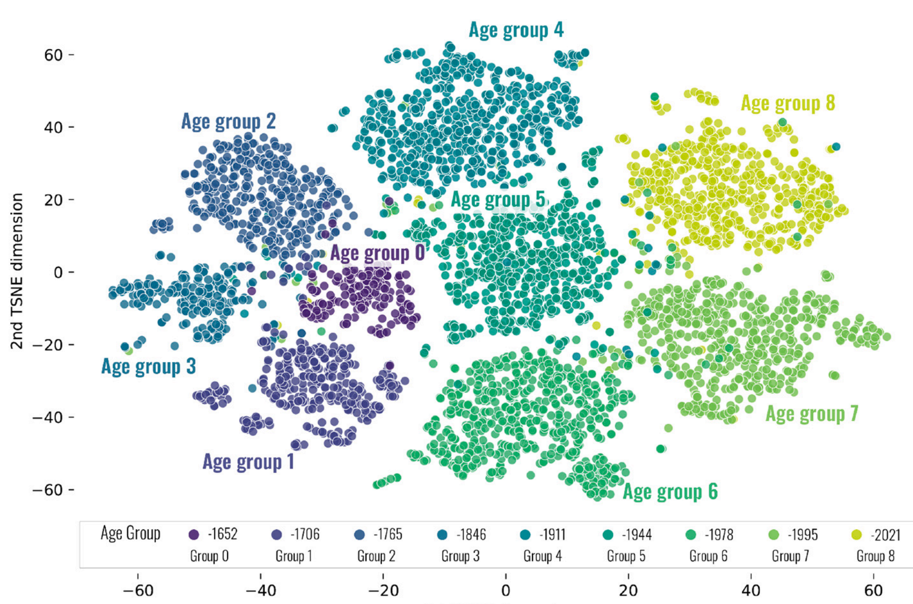

Fig. 11. Deep features of each image are projected onto a two-dimensional plane to understand what the model learned about the ages of the building.

early eras usually contain wider frames, more decorations and are narrower. From 1911–1943, square and horizontal windows show up with the thinner frames, less decorations and less depth.

5.2.3. What is the relationship among architectural styles?

We apply feature visualization to interpret what the model learned about age information and the relationship among building styles. Deep feature vector of each image sample is obtained from the model and projected onto the two-dimensional plane with t-SNE. As shown in Fig. 11, the color represents the age group each point belongs to. The projected points automatically form 9 clusters with clear boundaries. With dark colors representing old ages and light colors indicating recent eras, it is worth noticing that clusters with similar colors are also close to each other in the two-dimensional plane. This shows that the building age epoch prediction model is able to capture meaningful age-related information from images. The age group 0, which is the oldest era in our research, is adjacent to not only similar age groups (1, 2 and 3), but also age group 5 and 6. This indicates similarities of architectural elements in these periods and an architecture revival movement in the early 20th century. Generally, the clear pattern demonstrates the ability of our model to learn and extract age-related information from images and distinguish among building age groups.

5.2.4. What is the relationship between building age and style?

In most cases, architectural styles are associated with specific time periods. Here, we explore the detailed evolution of architectural styles by inspecting the distribution of building styles within each building age group. As shown in Fig. 12, color represents the style group each point belongs, which is the prediction result from our independent architectural style classification model. The position of the point indicates the age group it relates to, which is the classification result from our building age epoch classification model. The general pattern aligns with common sense that building styles are highly related to building ages. In early ages (Age group 0, 1, 2, 3, 4, ranging from 1300 to 1911), most buildings are classified into style group 2 (Late 19th-century Style, in light green), which usually appears in 1870–1910 and is characterized by substantial bay windows, heterogeneous ornamentation, and stained glasses. As the age groups become more recent, the percentage of style group 5 (Contemporary Style) increases, indicating the transition and adoption of the Contemporary Style.

6. Discussion

6.1. Street view images as a proxy for architecture history study

With the approach of the big data era, street view images are easier to access from both map services (Google,[5] and Baidu[6]), organizations (Amsterdam city government[7]), and crowdsourcing platform, which provides opportunities to measure and understand built environments and human-environment interactions. In terms of urban building information collection, compared with DSM and LiDAR, street view imagery approaches so far are more cost-effective and scalable.

The contribution of this work is that it not only shows the predictive ability of GSV and deep learning, but also how the decision process and analysis of the deep learning model could be applied in architectural history studies. With the combination of deep learning, GSV images could be used to explore the evolution of building styles over time. In this research, GSV images are used to classify building ages with high accuracy and transferred to other cities easily with a small number of ground truth samples. Because of the power of DCNN, little preprocessing is needed for our task. More importantly, the internal representation learned from the process is able to imply the architectural element style evolution.

6.2. Building age and style model as a hint for building styles evolution

The combination of the building age epoch and style model could be used as a hint for architectural style evolution. With our framework, we are able to trace the evolution of architectural elements such as windows, which is one of the most important architectural elements related to building styles (Shalunts et al., 2011; Xu et al., 2014). As discussed in Section 4.2.2, windows in early eras tend to be narrow, have wider frames, and with more decorations, while recent windows have more diversity in size, shape and depth.

Our method could also be used to trace the transition of architectural styles in temporal and geographical dimensions. In terms of temporal dimension, as shown in Section 5.2.4, the distribution of building styles within each age group is able to reveal the temporal pattern of adoption of new building styles. In the sense of geographical dimension, when we directly applied building age epoch model trained on Amsterdam to Stockholm, while the two cities have a similar distribution of building age data, the classification performance of modern eras is much higher than early ones. This indicates the buildings constructed after 1979 share similar architectural elements or characteristics in the two cities. As Kenneth Frampton argues that modern architecture is becoming more and more homogeneous (Foster, 2002), we could utilize building age prediction model to explore the temporal pattern of homogeneity and revisit classical theories about building styles.

6.3. Limitation and future work

The main limitation of our study is the bias of data collection. The construction year of buildings in BAG dataset is defined as "the year in which a building was originally or will be delivered as constructionally ready." Renovation, expansion and addition to the building do not change the original year of construction. This limitation is reflected in Fig. 8 that our age epoch estimation model yields less accurate predictions for Amsterdam city center, as buildings in the city center have higher possibilities to be renovated. In another sense, these misclassified samples are able to provide urban planners and policy makers insights about identifying and locating the renovated buildings. It is also beneficial for urban renewal, historical architecture preservation and gentrification. It is worth mentioning that our model chooses to ignore the first floor of buildings, which are more often renovated than other parts, while making decisions. The power of deep learning has helped us to avoid this limitation to some extent.

This study could be further developed in two directions. First, although this work focuses on a deep learning framework aiming at gaining knowledge about the age and style of buildings, this work does not conduct a thorough performance comparison between different deep learning-based prediction methods. The prediction could be further improved if more indicators are included. For example, previous studies often use morphological indicators (e.g., height, area, complexity of the footprint, etc.). Kang et al. (2021) explore combining morphological attributes, image and other multi-source data to predict housing price appreciation. The combination of all data sources contributes to higher prediction power. By considering the spatial dependence of building age attributes and including neighbor's building age, the performance could be further improved and better for real-world application. Second, this study could explore further on building style evolution. If multiple cities are included, the spatial transmission and temporal evolution of architectural styles might be articulated with our framework.

7. Conclusion

Traditional study on building styles and history is heavily realized on domain expertise and field studies. With the widespread application of

[5] https://www.google.com/streetview/.
[6] https://quanjing.baidu.com/.
[7] https://data.amsterdam.nl/.

Fig. 12. Distribution of building styles in age periods. Color indicates the style groups that the point belongs to, location represents age group. In more recent age periods (age group 7 and 8), Style 5 (Contemporary Style, in light yellow) has higher proportions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

data-driven methods in building environment studies, we propose an approach that applies a deep learning and computer vision for the study of architectural styles and history.

In this work, we propose a framework for understanding the relationship between architectural styles and building ages. Three components for building age and style interpretation are introduced in this framework. The building age epoch prediction method is tested on Amsterdam, Netherlands and Stockholm, Sweden. We also introduce a building style classification model and apply it to Amsterdam. By comparing the model performance of Amsterdam and Stockholm, analyzing the age epoch prediction model and combining the results of age epoch and style predictions in Amsterdam, we are able to trace the evolution of architectural element styles and architectural styles temporally and spatially. The age prediction model is able to achieve an overall accuracy of 81.09 %. The test in Stockholm shows that, with little ground truth samples, our model could be extended to other cities.

This study also addresses the potential street view images have for understanding buildings and built environment and the practical implications of our methods. We also explore the possibility of combining building age and style classification models to trace the evolution of architectural styles in temporal and geographical dimensions.

CRediT authorship contribution statement

Maoran Sun: Data Curation; Methodology; Data Analysis; Writing-Original draft, Reviewing and Editing; Validation.

Fan Zhang: Conceptualization; Methodology; Data Analysis; Writing-Reviewing and Editing; Project Administration.

Fabio Duarte: Manuscript Reviewing and Editing; Project Administration.

Carlo Ratti: Conceptualization; Funding acquisition; Supervision.

Declaration of competing interest

We declare that none of the authors have competing financial or non-financial interests as defined by Cities, Elsevier.

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