Mapping sense of place as a measurable urban identity: Using Street View images and machine learning to identify building façade materials

Abstract: Sense of place, as an intangible perception, is widely recognized as an urban identity and of great value in both cross-cultural studies and contemporary urbanism. Building façade material can effectively capture sense of place due to its combination of physical and social attributes. Nevertheless, there are no widely implementable and high-resolution approaches to identify façade materials on a large scale. As a response, this study proposes a method using Street View images (SVIs) and a set of deep Convolutional Neural Networks (CNNs) to identify building façade materials. Specifically, a large cross-cultural training set was built to promote generalizability. Buildings within SVIs were divided into high-resolution rectangular images and classified using a well-trained Residual Network-50 (ResNet-50) model. Sense of place and its spatial patterns were then depicted by measuring façade material and analytical indicators including diversity and continuity. Eight cities worldwide with distinctive urban identities were examined. The findings revealed that compared to Asian cities, New York City, Chicago, and London are similar, while Paris and Tokyo are more distinctive. While challenges persist in comprehensively measuring the sense of place, the analysis of façade materials offers an insightful indicator that can assist in enhancing urban identity for contemporary urbanism. This study not only promotes the fine development of urban science through the empowerment of intelligent algorithms but also introduces a new perspective on exploring unmeasurable qualities based on the objective physical environment.

Keywords

building façade material, sense of place, urban identity, street-view image, machine learning

1. Introduction

The concept of sense of place, as a combined perception of physical and social elements, has been regarded as a key issue of urban identity and thus widely discussed (Ziyaee, 2018). Although intangible, sense of place is grounded in the physical environment, with attached social meanings equally important (Ujang and Zakariya, 2014). This nature positions building façade materials as a crucial component in defining a sense of place.

Building façade materials serve as a well-suited medium that connects both physical and social elements, which makes it a critical element of the physical appearance and instrumental in shaping a place and its perception (Norberg-Schulz, 1980). Specifically, it defines the physical characteristics in terms of color, shape, line, and texture (García et al., 2006), with its utilization reflecting different social factors, including traditions, history, and local culture (Calle, 2020; Golden, 2017). For example, the transition from brick to glass façades in the Manhattan skyline not only transforms physically but also symbolizes the formation of modern cultural memory. Besides, building façade material exhibits considerable controllability and designability in urban design and planning, underscoring its crucial role in place-making. Consequently, the identification of façade materials is a key element of the built environment. It reveals sense of place by connecting physical and social dimensions. This reflects urban identities at a cultural level, as shown in Appendix I.

To map sense of place and its spatial patterns effectively, a detailed large-scale analysis of façade materials is essential. Combining Street View Images (SVIs) with deep Convolutional Neural Networks (CNNs) offers a promising alternative to costly and time-consuming manual methods. The usability of SVIs has already spurred progress in large-scale quantitative urban studies (Biljecki and Ito, 2021). Furthermore, CNNs enable precise semantic analysis and feature learning on SVIs, efficiently handling large-scale data with strong generalization (Alzubaidi et al., 2021). These advancements have led to widespread trends in urban element extraction and urban quality assessment (Zhang et al., 2020; Liang et al., 2023).

Using machine learning algorithms to analyze façade materials in SVIs presents a viable approach. However, existing methodologies lack specificity and fail to enable a precise and wide-scale assessment of sense of place. The primary objective of this study is to establish a transferable approach to identify façade materials at high resolution and map sense of place as an urban identity on a large scale.

2. Related studies

2.1. Existing approaches to measure façade materials

Previous methods used to measure façade materials have struggled to balance high precision and large scale that are essential for mapping the sense of place. Two main approaches have been proposed: The first includes the top-down estimation methods, such as using material flow statistics to assess stock changes over a specified period (Tanikawa et al., 2015). These methods are more aligned with regional inventory statistics rather than spatial mapping. They lack the resolution necessary to analyze the external materials of buildings at specific geographic coordinates, which is essential for sense-of-place studies. The second approach involves a series of data acquisition techniques, e.g., hyperspectral and multispectral imaging (Zahiri et al., 2022), laser scanning (Uotila et al., 2021), and mobile-device-based Lidar scanning (Gordon et al., 2023). Methods like machine vision algorithms are then employed to extract material information. Despite their high precision, these methods are impractical for large-scale urban applications due to the high costs and challenges of implementing these devices on an extensive scale.

2.2. SVIs and deep learning algorithms: Progress and challenges

In the last few years, SVIs and deep learning algorithms have been used to measure the physical environment (Biljecki and Ito, 2021), highlighting the potential for balancing large-scale and high-precision applications compared to previous methods. Early studies primarily employed traditional computer vision algorithms to identify integral aspects of the built environment, e.g., street greening (Li et al., 2015) and the Sky View Factor (Zeng et al., 2018). With the advancement of machine learning, deep learning algorithms like CNNs enabled more specialized and high-precision measurements. They are widely used in computer vision for tasks such as semantic segmentation, classification, and detection (Guo et al., 2016). These applications enable the quantification of nuanced environmental attributes, e.g., pedestrians (Chen et al., 2020), façade color (Zhou et al., 2023), and building age (Sun et al., 2021).

Recent research has emerged on discerning material-related information from SVIs. Zhou and Chang (2021) have employed various machine learning techniques to classify building structures. Hosseini et al. (2022) have developed a framework to identify sidewalk materials. The datasets in these studies are confined to specific cities or countries, with insufficient focus on façade materials. Raghu et al. (2023) successfully classified building façade materials in SVIs, yet the resolution was inadequate for detailed analysis of material composition within individual SVIs. The small number of annotated samples also hampers cross-cultural analysis, as it constrains the model's ability to capture broader data distributions. Additionally, the whole-image annotation approach impedes the identification of intrinsic material features, given the significant visual variation among building forms with different façade materials.

In conclusion, the primary research gap is the absence of an effective methodology for identifying façade materials with the resolution necessary to accurately depict a sense of place. The current methods fail to capture detailed material composition of building façades and the classification models lack focus on the intrinsic features of the materials. Moreover, there is a lack of a generalizable approach for robust cross-cultural studies on urban identities.

Thus, to support the analysis of sense of place, the initial step is to construct a high-resolution classification framework for façade materials that reflects detailed visual information related to a sense of place. Additionally, it is necessary to increase its generalizability by compiling a cross-cultural dataset with extensive annotated samples. By developing a deep learning-based methodology to measure city-scale building façade materials from SVIs, this study aims to map sense of place as a measurable urban identity.

3. Methodology

3.1. Research framework

The methodology flowchart is shown in Figure 1. The approach involves training a model for the identification of façade materials and mapping sense of place against the distribution and spatial pattern of collected material data.

The methodology comprised five steps: data mining, preprocessing, dataset building, model training, and large-scale deployment. First, SVIs provided by data vendors were collected. Second, preprocessing, which involved semantic segmentation of building façades and their division into rectangular units, was conducted. Third, a cross-city dataset was built by labeling the divided images. An augmented dataset was also created using augmentation algorithms. Fourth, a pre-trained deep learning model was employed for training, following which the effectiveness of the best model in real applications was validated. Finally, the trained model was used to classify SVIs from the study area and the distribution of building façade materials is presented, based on the results. The analytical indicators, diversity, and continuity, were also calculated to further explore the spatial pattern of sense of place. The final analysis was divided into two parts to demonstrate support for cross-cultural research and contemporary urbanism.

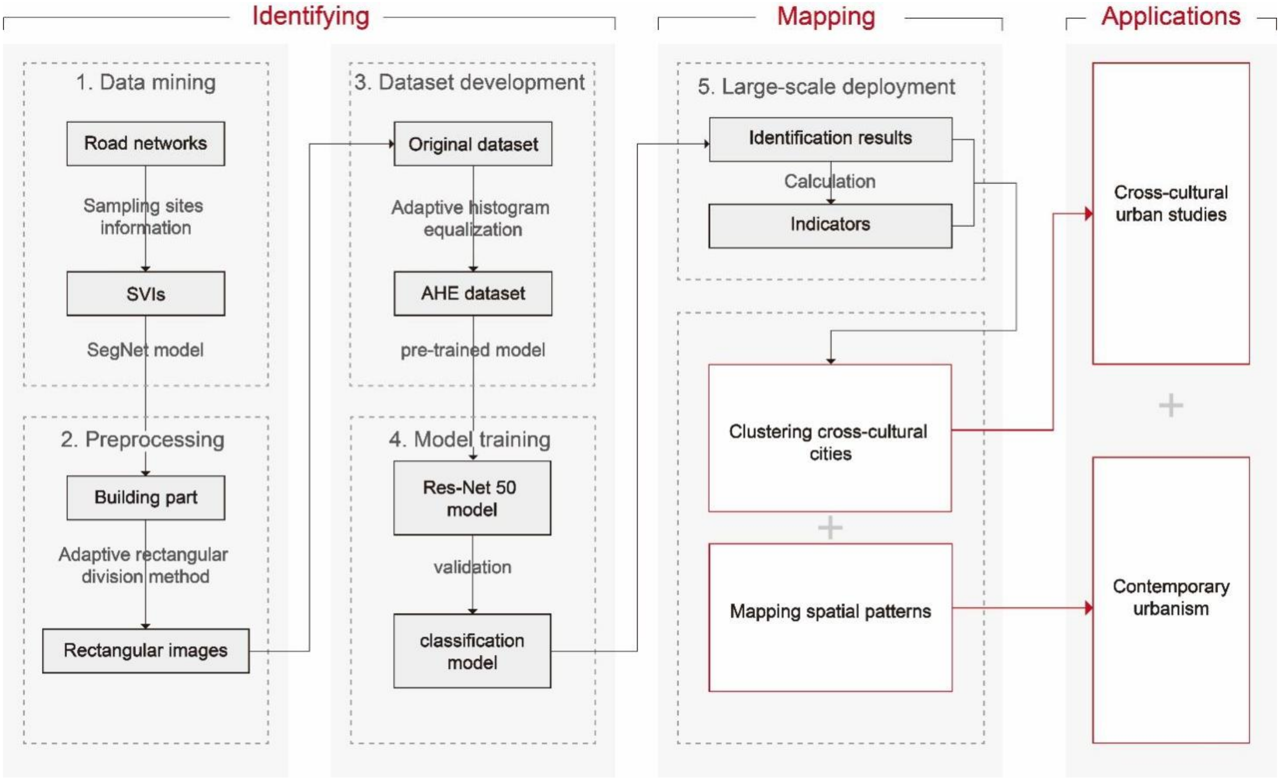

Figure 1. Workflow diagram.

3.2. Research area and data mining

The research area shown in Appendix II includes London (LON), New York City (NYC), Singapore (SIN), Hong Kong (HKG), Shanghai (SHH), Paris (PAR), Tokyo (TKY), and Chicago (CHI). The selection of these cities was guided by criteria encompassing both the Globalization and World Cities (GaWC) ranking in 2020, and the representativeness of regional cultures across Europe, North America, and Asia (Gupta et al., 2002). The scope of analysis for each city was delineated using its administrative center or prominent landmark as the center, with a radius of 15 kilometers. This spatial extent can be considered to encapsulate the most distinctive built environment of a city. These cities were analyzed to showcase the potential for cross-cultural urban analysis of our study. Additionally, the entire city of NYC was analyzed separately to demonstrate the ability to support contemporary urbanism by mapping sense of place and its spatial pattern.

The road network data utilized in this study was acquired from the OpenStreetMap website.

Sampling sites were generated at 200–300m spacing within ArcGIS, encompassing latitude and longitude. The SVI associated with each sampling site was automatically retrieved from the application programming interface service. Due to data availability, most of the SVIs were obtained from Google, while those of SHH were sourced from Baidu Maps. To minimize any potential bias for identification, the collected SVIs were exclusively captured from a vertical street perspective.

3.3. Preprocessing

The preprocessing procedure is illustrated in Figure 2(a)-(e). The initial involved extracting building façades. Each SVI consists of 1024×1024 (height×width) pixels. For Google SVIs, a fisheye correction had to be applied. Subsequently, a pre-trained SegNet (semantic segmentation) model (Ye et al., 2019) was employed. The pixels identified as building façades were extracted to eliminate interference from non-building pixels in SVIs. Only images with building façade areas exceeding 20% were retained. The lower one-third of the image was then cropped to eliminate interference from pixels of the occasional road.

To improve the resolution and the attention to detailed features, decomposing building façades into rectangular units is a proven and effective approach (Doersch et al., 2012). In this study, we proposed an adaptive rectangular division method. Through repeated testing, rectangular sizes of 100×100, 80×80, and 60×60 (height×width) in pixels were selected to accommodate different building façades. These rectangles would traverse and fill all non-black pixel graphics, with a preference for larger sizes. This configuration ensured that most rectangles in the images could effectively represent a single texture without compromising computational speed. Divided rectangles served as the fundamental unit for material measurement, isolating material properties from extraneous environmental variables and yielding high-resolution identification outcomes.

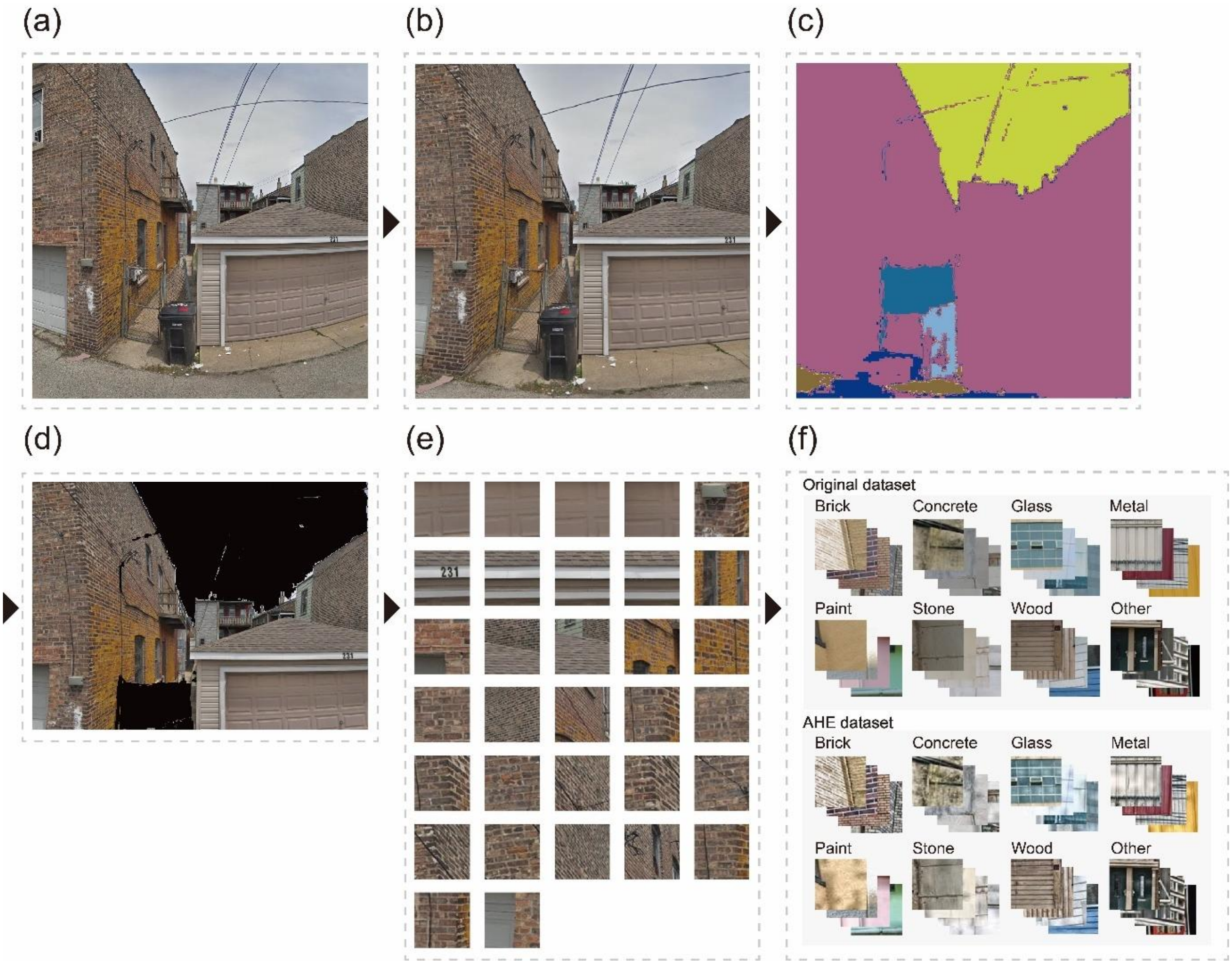

Figure 2. An illustration of preprocessing and dataset building: (a) Raw SVI; (b) Fisheye lens distortion correction; (c) Semantic segmentation; (d) Extraction of building façades; (e) Adaptive division of rectangular units; (f) Examples of images from the original and the AHE datasets.

3.4. Dataset development

The divided rectangles used for annotation were randomly sampled from the collected SVIs and ensured a roughly uniform sample size from each city. This study defined seven façade material classes, including brick, concrete, glass, metal, paint, stone, and wood. Images with multiple or unidentified materials were excluded during labeling, and an "Other" category was created to include doors, windows, and various interfering elements. Furthermore, this study incorporated random rotation, exposure adjustment, and mirroring techniques to expand the dataset and enhance its robustness.

In addition to the original dataset, an augmented one was generated for comparison. Commonly employed in computer vision, adaptive histogram equalization serves as an image enhancement algorithm (Stark, 2000). It is effective in not only addressing local brightness variations but also, ultimately, enhancing image details and clarity. The new dataset was named adaptive histogram equalized (AHE) dataset. The original and AHE datasets are shown in Figure 2(f).

3.5. Model training and validation

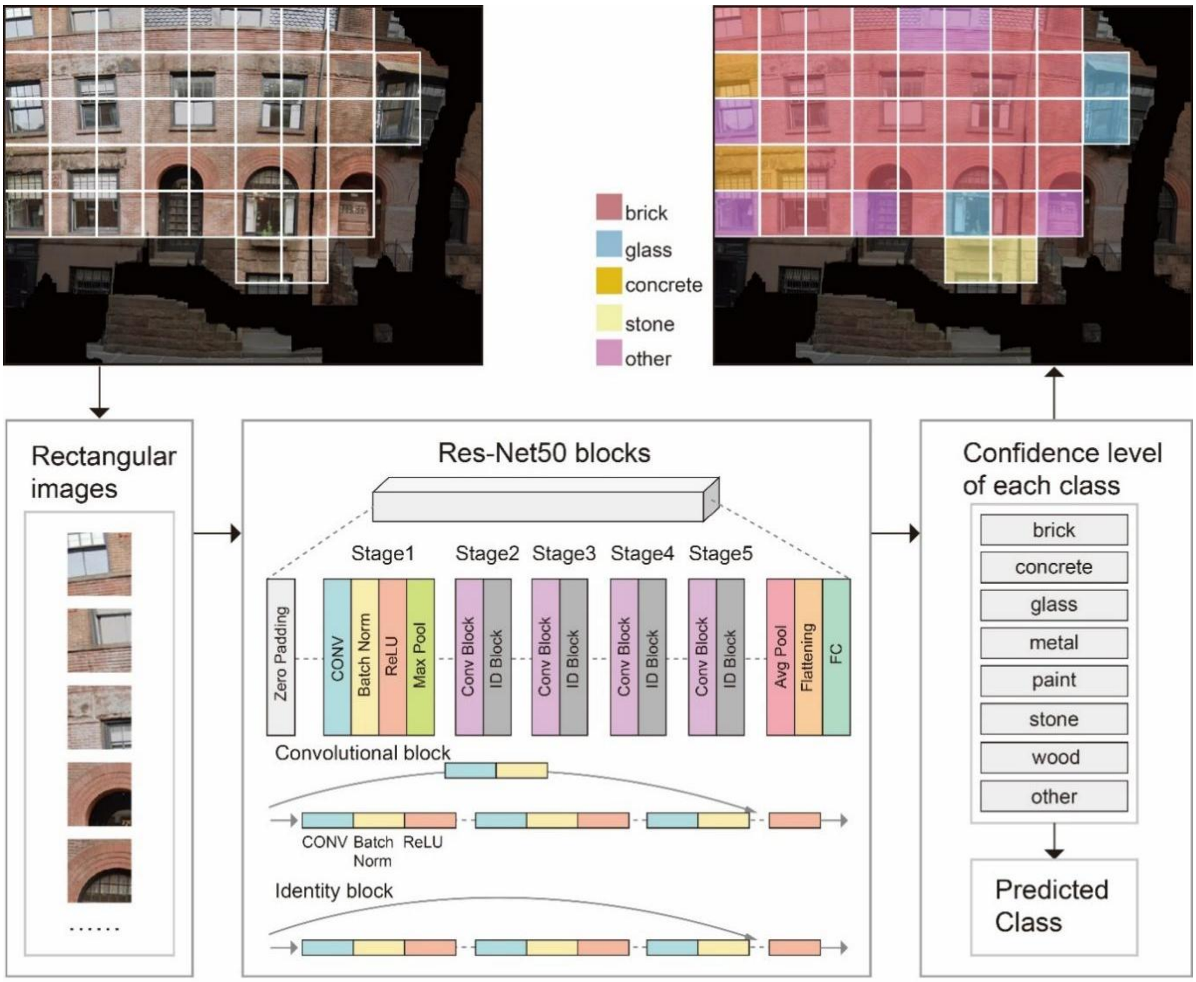

Figure 3. The process of training the FMCM using ResNet-50.

Due to adequate preprocessing, the task was converted to a typical feature classification. As shown in Figure 3, the façade materials classification model (FMCM) was trained using Residual Network (ResNet) architecture with 50 layers. It is a widely used type of Convolutional Neural Network (CNN) architecture incorporating residual learning. By introducing skip connections across layers, ResNet enables the learning of residual functions, thereby facilitating the optimization of deep networks (He et al., 2016). Additionally, a pre-trained image classification model on ImageNet-21K was incorporated during the training process to enhance performance. The results from model training were compared with the performance of the original and AHE datasets to select the most promising model for subsequent applications. Random selection was used to allocate 90% of the images for training and 10% for validation in both datasets. The subsequent model training and application phases were conducted on a system equipped with an NVIDIA A16 GPU with 15GB of RAM, complemented by three Xeon Gold 5318Y CPUs.

The hyperparameters of the FMCM model were fine-tuned for optimal performance, including a batch size of 128 and 20 training epochs. The learning rate was dynamically adjusted during each epoch, starting at 0.001 and halving every three epochs until it reached 0.0000625. Additionally, fine-tuning determined a 25% dropout rate in the full connection layer, optimizer AdamW, and the cross entropy loss function as the hyperparameters. The primary metrics for performance evaluation included accuracy, precision, recall, and the F1 score. Models were also evaluated based on their computational efficiency. The final model selection was made by considering a trade-off between these factors, aiming for a model that exhibits both high predictive performance and practical applicability.

Finally, to confirm its practical usability, an additional validation process was conducted, as shown in Appendix III. First, three street view images from each city were randomly chosen for manual pixel extraction of various materials in Photoshop, serving as a benchmark. The proportions of materials identified by the FMCM were then compared to these manual assessments, computing Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Second, 60 street views were randomly selected. Two domain experts annotated the dominant materials that influence the sense of place. These results were then compared to the model's recognition performance to further verify whether the proposed method could adequately substitute for manual evaluation in terms of accuracy.

3.6. Large-scale deployment

All rectangular images divided from SVIs were classified by FMCM. In addition, considering expert judgment, images with generally low confidence levels were classified as "Other." When different materials were in nearly equal proportions, the material of that sampling site was recognized as "mixed."

Following classification, diversity was calculated using formula (1) of the Shannon index, commonly used in visual studies of the built environment (Yap et al., 2023). M is the number of different species and P_i is the proportion of individuals belonging to the i^{th} species. In this case, M is the number of different classes of façade materials. The level of diversity indicates the degree of mixing of different materials in a place.

$$H = \sum_{i=1}^{M} P_i \ln(P_i) \quad (1)$$

Local Moran's I was utilized to measure continuity, capturing the local aggregation of space. Local Moran's I is defined as formula (2) where x_i denotes the variate value at the location i and $\bar{x}$ is the average value of x with the sample number of n. S_i^2 is the variance of variable x, and $w_{i,j}$ is the weight that was defined as the inverse of the distance $d_{i,j}$ among locations i and j. Because each sampling site had eight different classes, the continuity was calculated according to formula (3) where M represents the number of façade materials category. A positive continuity suggests material aggregation of similar classes, while negative continuity implies dispersion within similar classes.

$$I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{i,j}(x_j - \bar{x}) \tag{2}$$

$$C = \frac{\sum_1^M I_{i,M}}{M} \tag{3}$$

In addition to the various calculations for each sampling site, an analysis of the overall material distribution was also performed. Diversity was still calculated based on formula (1). To evaluate the overall continuity, Global Moran's I was employed. This statistical measure can assess spatial autocorrelation (Westerholt, 2023), which helps in characterizing the clustering or discrete trends exhibited by the façade materials within the city. The global version of Moran's I is given as

$$I = \frac{\mathrm{n}}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{4}$$

where x_i denotes *n* sampling sites with mean $\bar{x}$ that are spatially connected via weights $w_{i,j}$. The I_M corresponding to the different classes was similarly summed according to formula (3) for the overall continuity.

Identification was then followed by statistical analyses, including classification, diversity, and continuity of sense of place, in addition to clustering evaluations for central urban areas across eight cities. Hierarchical clustering is a common algorithm that can group data into clusters without requiring a predefined number of clusters (Song et al., 2020). This approach offers significant flexibility, allowing for the recognition of patterns within the data structure. We calculated the Euclidean distance between eight cities as a measure of similarity, based on the proportions of different materials as well as their diversity and continuity. Subsequently, agglomerative hierarchical clustering was applied. For NYC, mapping was performed separately for classification, diversity, and continuity to identify potential distribution patterns of sense of place.

4. Results

4.1. Training and validation

A total of 348,094 SVIs were collected from the central areas of eight cities, with 84,560 from all of NYC. The adaptive rectangular dividing method was employed to process the fitting images. Random selection, manual screening, and labeling yielded a dataset of 17,914 rectangular images. After augmentation, the dataset size increased to 26,355, with 2500–5000 images of each class, ensuring no class imbalance. The size of the AHE dataset matched that of the original dataset.

Subsequently, ResNet-50 architecture was employed for training on both datasets. The classification process was efficient, with an average processing time of less than one second per SVI. No overfitting occurred during training, as shown in Appendix IV. The FMCM trained on the AHE dataset achieved a validation accuracy and metrics like precision, recall, and F1-score of approximately 0.987. This outperformed the original dataset model by around 0.02, as detailed in Appendix V. These improvements highlight the AHE model's superior accuracy and completeness in class prediction. Consequently, the model trained with the AHE dataset was selected for subsequent research applications, owing to its enhanced feature extraction and generalization capabilities.

The FMCM trained with the AHE dataset was then validated. First, the FMCM demonstrated high accuracy in façade material extraction. It achieved an average MAE of 0.06 and an average MAPE of 0.20, which reflects a low error rate in its prediction. Second, the model's predictions for the sense of place closely aligned with expert evaluations, achieving an accuracy rate of 0.89. Consequently, this level of performance was deemed sufficient to supplant manual categorization in future large-scale classification endeavors.

4.2. Mapping sense of place based on building façade materials

4.2.1. Mapping and cross-cultural analysis in sense of place across eight cities

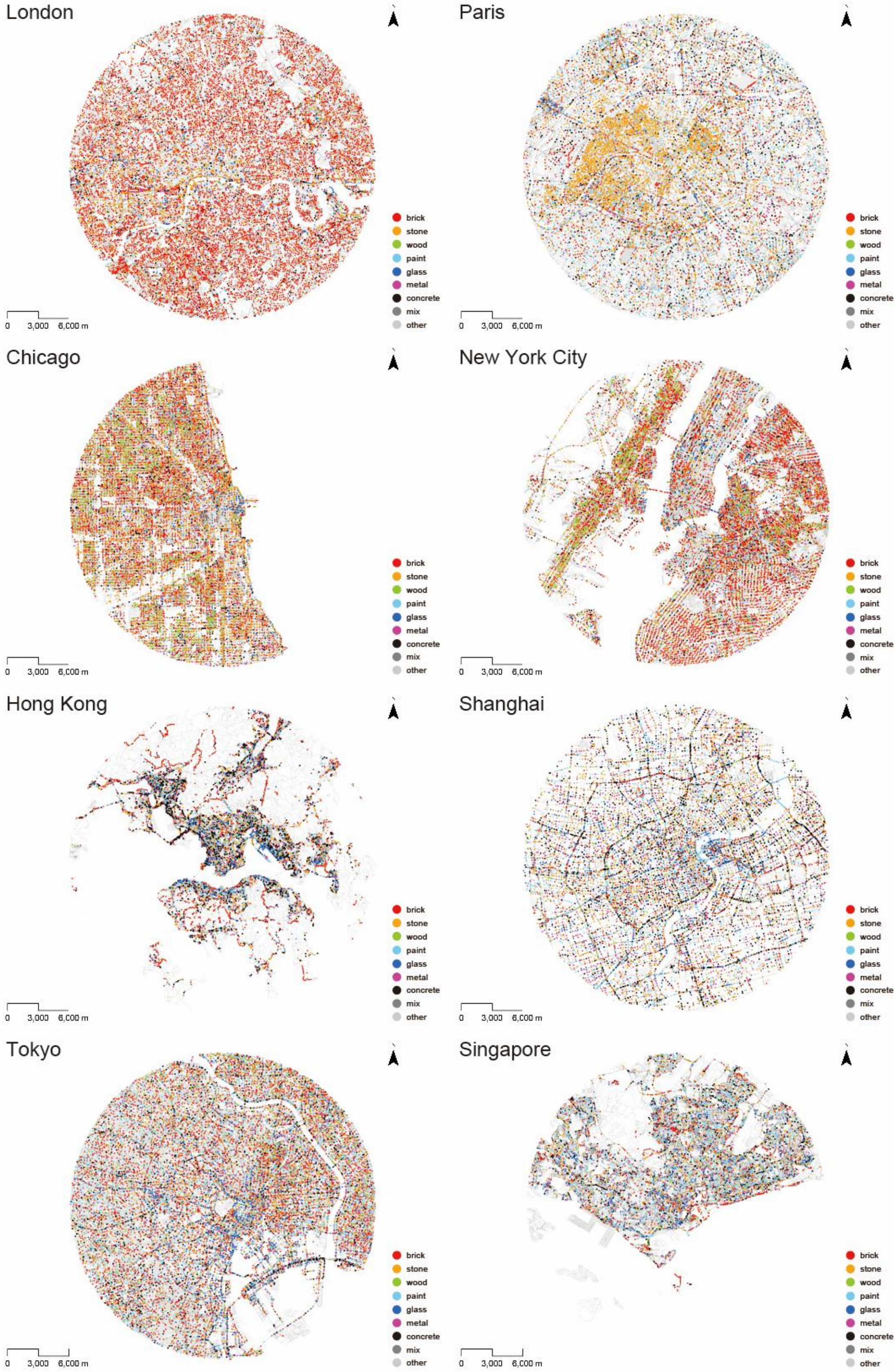

Figure 4. Mapping spatial distributions of the sense of place across eight cities using SVIs and a well-trained FMCM.

Based on the identification of façade materials, sense of place across eight cities was mapped, as shown in Figure 4. Specifically, in London, bricks are widely distributed throughout the city. On the north bank, stone façades are more prevalent. In Paris, extensive stone-dominated areas are distributed across the urban center, while the new area in the northwest utilizes more glass. Both Chicago and New York City are characterized by brick. However, in their residential areas, many streetscapes are dominated by wood. In Hong Kong, the dominant materials are glass and concrete, which are also widely used in other Asian cities. In Shanghai, glass façades are particularly evident in the new development area on the east bank. Tokyo exhibits similar characteristics in new areas, although there are more brick façades in the city. In Singapore, glass-dominated places are not isolated but spread throughout the city.

Figure 5(a) depicts some examples of prediction and Figure 5(b) displays the statistical results, indicating that among all the cities, LON has the highest proportion of brick, followed by NYC and CHI. PAR has significantly higher proportions of stone compared to other cities. Glass is generally more prevalent in the four Asian cities than in Europe and North America. Additionally, SIN has the highest proportion of paint, while SHH and HKG are dominated by concrete. On the contrary, wood and metal have generally low proportions. With regard to diversity in sense of place, TKY has the highest value, followed by PAR, NYC, and HKG. Concerning continuity in sense of place, PAR has the highest value, followed by SIN, while TKY has the lowest.

Figure 5. (a) Examples of model predictions and corresponding SVIs. Left to right: dominant material, diversity, and continuity. (b) Statistical results of classification, diversity, and continuity in sense of place across eight cities.

Figure 6(a) reveals that HKG, SHH, and SIN are the most similar cities, followed by NYC and CHI. LON and SHH exhibit the greatest differences. Figure 6(b) presents the results of hierarchical clustering. Using the elbow method, a notable slowdown in the Sum of Squared Errors (SSE) decline when dividing into four clusters suggests this is the optimal categorization. It is clear that Anglo and Asian cities form two typical regional clusters, while TKY and PAR are more unique, each forming a distinct cluster.

The results reveal the possible cultural mechanisms influencing urban identity differentiation. Differential urban modernization processes may explain the variations in Anglo and Asian clusters. Europe and America underwent the Industrial Revolution and modernization earlier. The lengthy urban renewal phase resulted in a higher blend of old and new places (Gandy, 2003). In contrast, Asian cities underwent modernization later but at a faster pace. Thus, their planning strategies created a predominantly unified modernist built environment (Rowe, 2005). In comparison, the urban identities of TKY and PAR are more influenced by geography, culture, and history. For example, high continuity in PAR is linked to the profound impact of Haussmann's renovation period, marked by unifying architectural styles and stone façades.

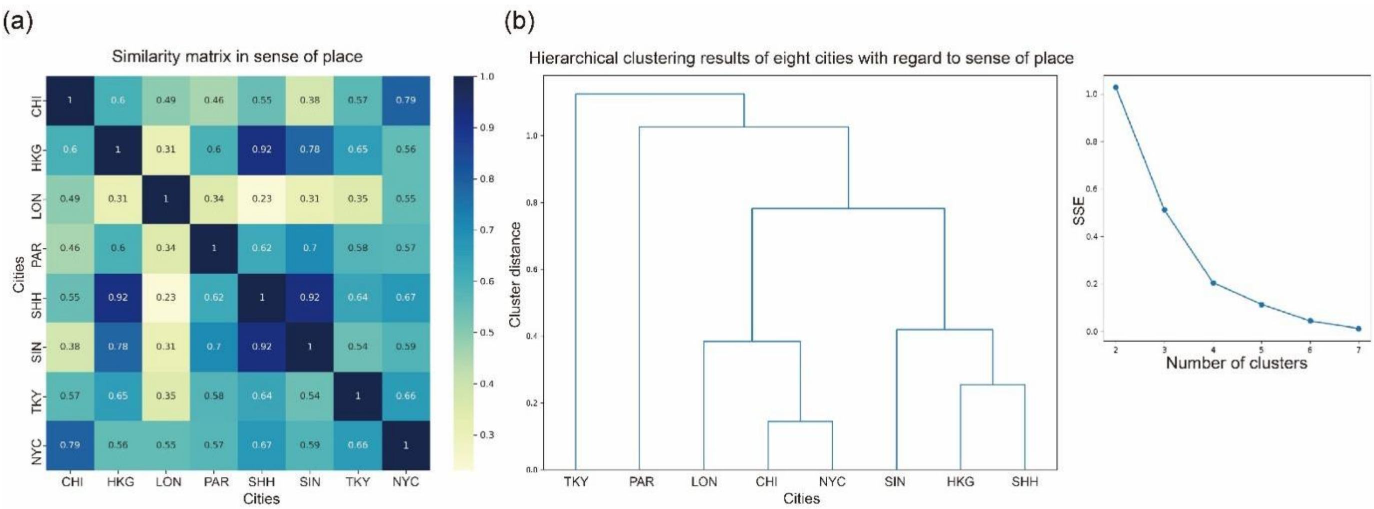

Figure 6. (a) Similarity matrix showcasing the comparison based on proportions of different materials, diversity, and continuity. (b) Hierarchical clustering results illustrating the grouping of cities with respect to their sense of place, with the optimal number of clusters determined through the elbow method.

4.2.2. Mapping sense of place and its spatial patterns in New York City

The analysis of NYC demonstrated the potential ability of our approach to assist regional policies and urban design guidance. Figure 7(a) shows the distribution of different façade materials in NYC. Across NYC, brick is the dominant material, while Manhattan stands out for its glass curtain walls. Clusters of wooden façades are prominent in residential areas in Queens and Brooklyn. Comparative analysis of the NYC household income map (Bai et al., 2023), can inform regional policy. It pointed to a higher incidence of glass and stone facade materials in upper-income neighborhoods, such as those in Manhattan, and parts of northern Brooklyn and Queens.

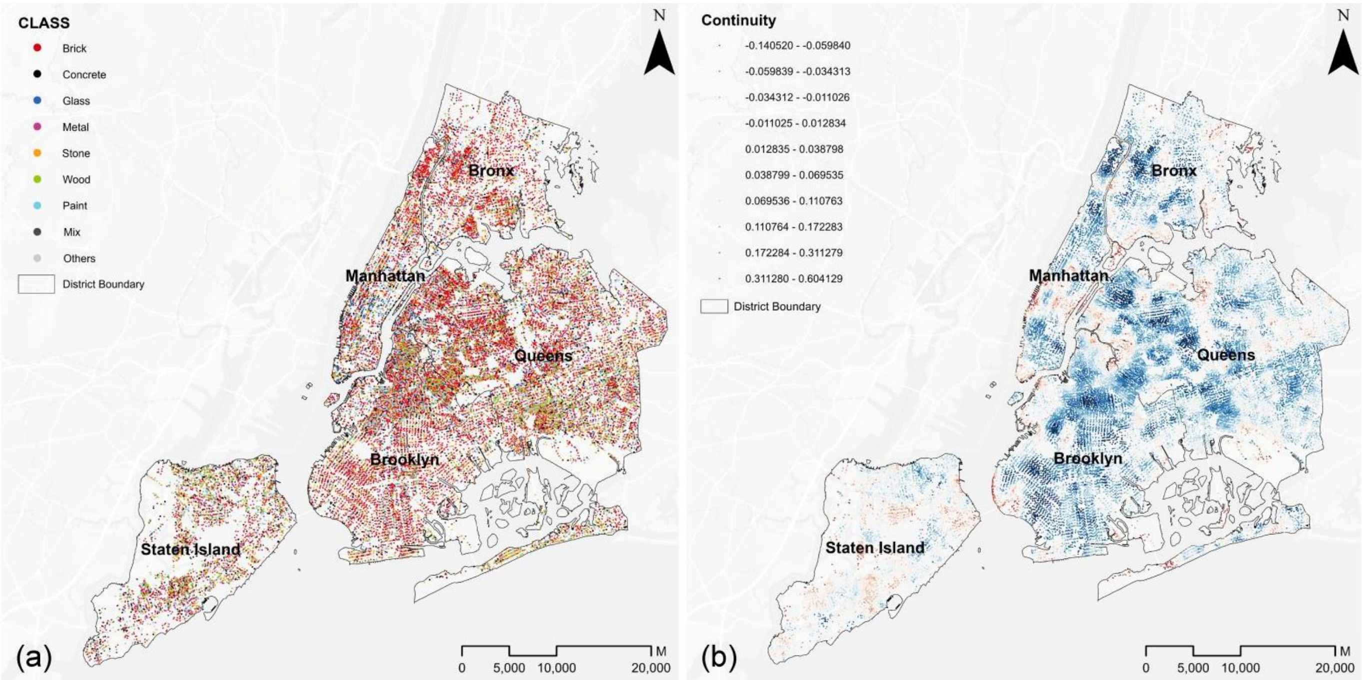

Figure 7. (a) Distribution of different façade materials in NYC using collected SVIs and well-trained FMCM. (b) Spatial pattern of continuity in sense of place of NYC based on the detailed measurement of façade materials.

Although no distinctive patterns of diversity were observed, Figure 7(b) illustrates the clear spatial pattern of continuity in NYC. The Financial District and Midtown in Manhattan have the highest level of continuity. The continuity is high along the northwest edge of Brooklyn and Queens, tapering off towards the periphery. Relevant policies may be positively influenced by comparisons of regional variations such as race distribution (Maantay and Maroko, 2009). For example, white and Hispanic neighborhoods were found to display higher continuity in sense of place compared to Brooklyn and central Queens, housing black neighborhood.

A comprehensive and detailed mapping of sense of place can also serve as the digital foundation for urban planning strategies. For instance, the southern end of Newtown Creek marks the end of continuous sense of place on the Queens-Brooklyn border. Future urban planning could focus on renewal initiatives at this juncture to extend the sense of place southward, with strategic guidance on facade materials enhancing this continuity.

5. Discussion

5.1. Mapping intangible sense of place as a measurable urban identity

Using an innovative analytical framework, this study explored the long-standing and widely discussed issue of the objective description of an intangible sense of place. Through large-scale and high-resolution analysis, façade materials, possessing both physical and social aspects, served as a key to mapping sense of place. This exploration helped transform sense of place from an abstract concept into an intuitive insight. Furthermore, mapping sense of place can now be recognized as a measurable spatial urban identity, which was previously only reflected in the experiences and imaginations of citizens.

5.2. Methodological improvement on building façade material identification

This study employed a systematic approach to identify building façade materials that combined urban range and fine-scale measurements. An intelligent framework was established using a series of deep-learning algorithms. By proposing an innovative classification method based on rectangular analysis units and constructing a large dataset, this approach overcomes previous limitations of resolution and generalizability. Moreover, this study showcases the path of integrating multiple intelligent methods to deeply mine the information embedded in SVIs. This direction focuses more on the capability and depth of analysis, which can facilitate the development of urban science toward finer granularity.

5.3. Contributions to cross-cultural urban studies and contemporary urbanism

The objective depiction of sense of place is valuable for cross-cultural urban studies in understanding urban identities from different cultural contexts. Sense of place as an environmental urban identity reveals the global cross-cultural clusters and genealogy of relationships between cities. This study introduces the potential to integrate humanities and social elements with a computational approach. This measurement will interpret the influence of different factors on shaping sense of place and related urban identities in the process of urbanization and globalization.

The intelligent depiction of sense of place and its spatial pattern also provides valuable assistance for contemporary urbanism in place-making. On one hand, this method can help identify the dominant building façade materials in certain areas, which can be converted into rules in zoning code. For instance, this method can precisely identify the extent of historic districts in London that are characterized by stone or brick materials. This allows urban design guidelines to mandate the selection of façade materials for new buildings that harmonize with historical façades. On the other hand, dynamic monitoring platforms can be established to track adherence to local façade material guidelines and the evolving sense of place. This approach can facilitate public participation, decision-making, and the evaluation of design programs. Overall, this study provides an objective presentation of results to inform decision-makers and planners.

Moreover, façade materials are widely recognized as intrinsic to the sustainability of a building, influencing the building's lifecycle and thermal performance. Therefore, the large-scale and efficient measurement of façade materials in our study contributes to evaluating the sustainability of the built environment. This can guide sustainable urban renewal strategies. Documenting façade materials also offers a novel approach to enable a more comprehensive assessment of urban vulnerability and resilience, providing detailed data for urban disaster risk management.

5.4. Limitations and future directions

First, the classes of façade materials discussed in this study were limited due to the challenges posed by building a larger dataset. A more comprehensive and refined classification system should be proposed in the future, facilitating a more nuanced depiction of sense of place. Second, although the adaptive rectangular division method proposed in this study performed well in handling most SVIs, its adaptability to distant buildings with unclear material features needs optimization. Alternative preprocessing methods that can enhance the features of long-distance façade materials should be integrated into the current process to mitigate this problem.

Third, future work should further integrate qualitative research with quantitative methods. Qualitative studies offer a fundamental framework for researching sense of place, enhancing the comprehensiveness and depth of measurement. Meanwhile, quantitative approaches to mapping sense of place can potentially yield new insights that improve qualitative research in turn. In future research, we plan to perform a more extensive survey in multiple cities across all cultural areas. This measurement will help us understand the interaction between physical and non-physical social issues, providing a big picture for advancing digital humanity and computational sociology.

6. Conclusion

This study introduces an innovative method to map sense of place as an urban identity by measuring façade materials. Specifically, we proposed an automated extraction methodology to identify building façade materials using deep learning models and SVIs, applying it to eight different cities worldwide. Simultaneously, based on the material information and analytical indicators, sense of place was visualized on a large scale, rendering this intangible concept recognizable. The measurement of sense of place introduces a new perspective for cross-cultural analysis through the examination of differences in urban identities across cities.

Additionally, it provides a data-driven decision-making approach for shaping urban identities by integrating the distribution of a sense of place and façade materials as controllable elements in urban planning. This study demonstrates the potential for the urban qualities of culture to be measured through the physical environment. It shows great promise in combining urban studies, computer technology, and humanistic thinking.

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Appendix I

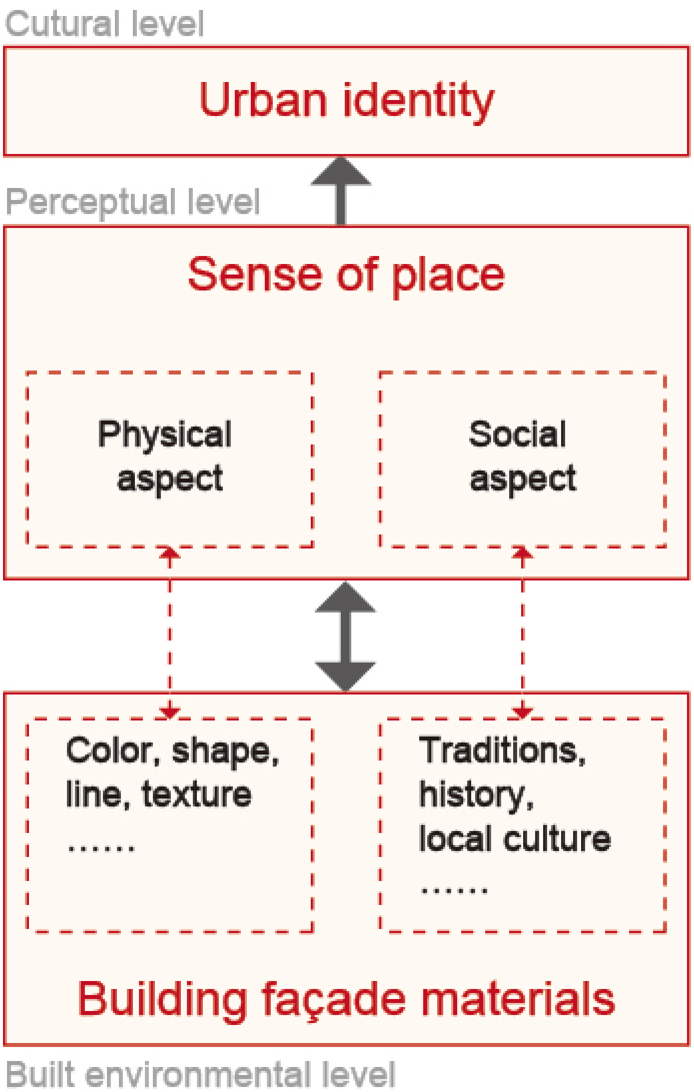

Figure 8. Conceptual framework.

Appendix II

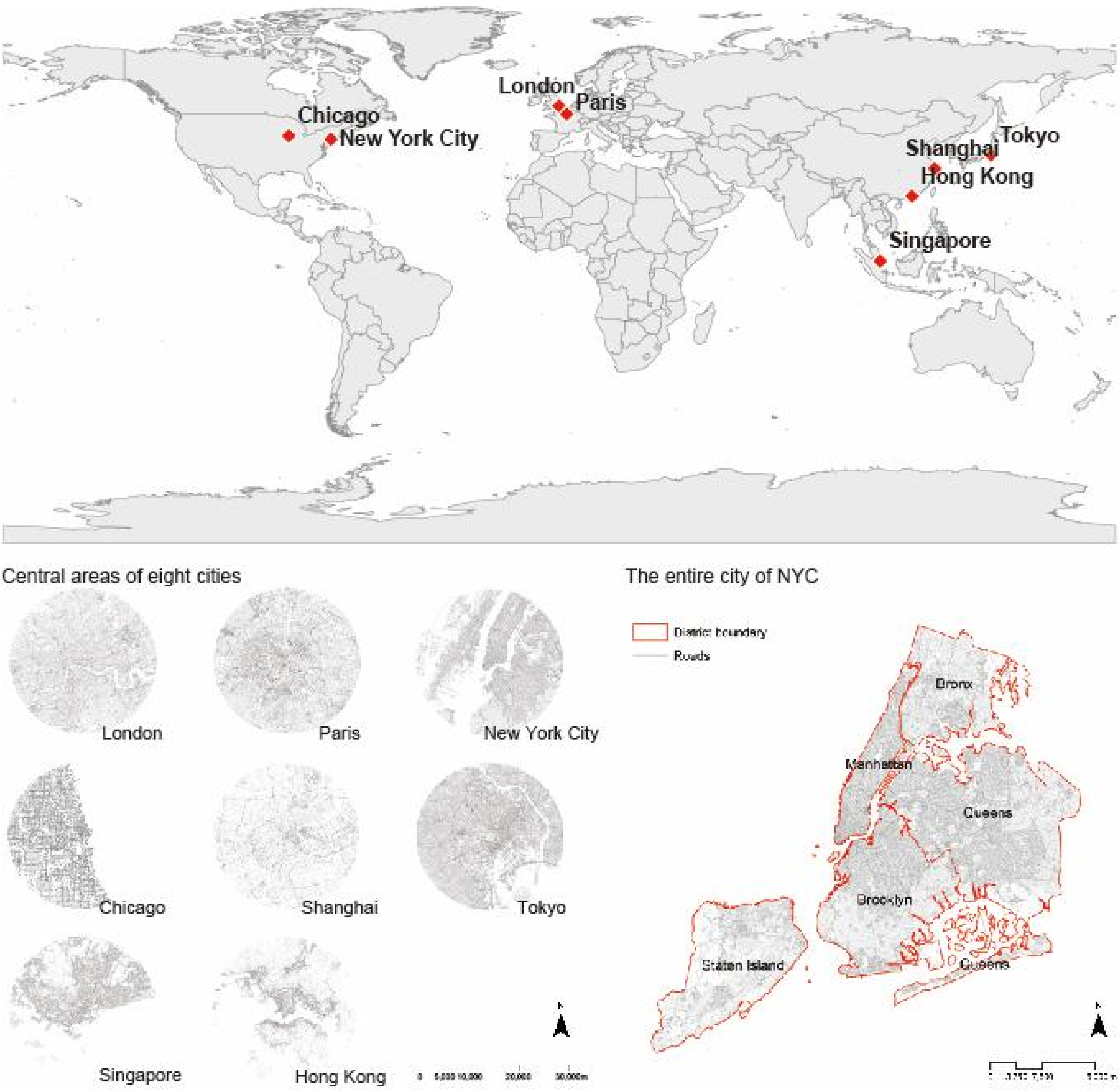

Figure 9. Research areas: the central areas of eight cities worldwide and the entire city of NYC.

Appendix III

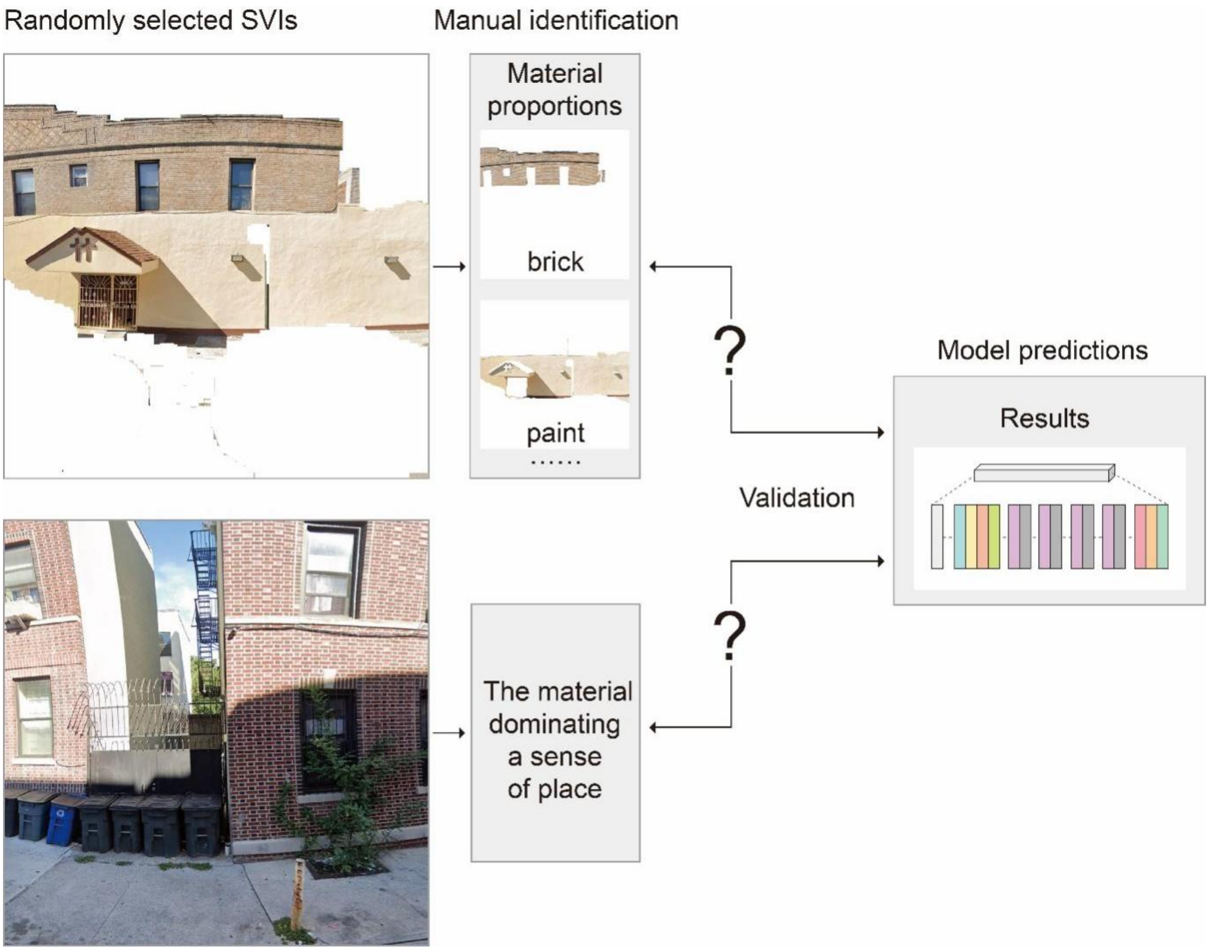

Figure 10. The process of validation.

Appendix IV

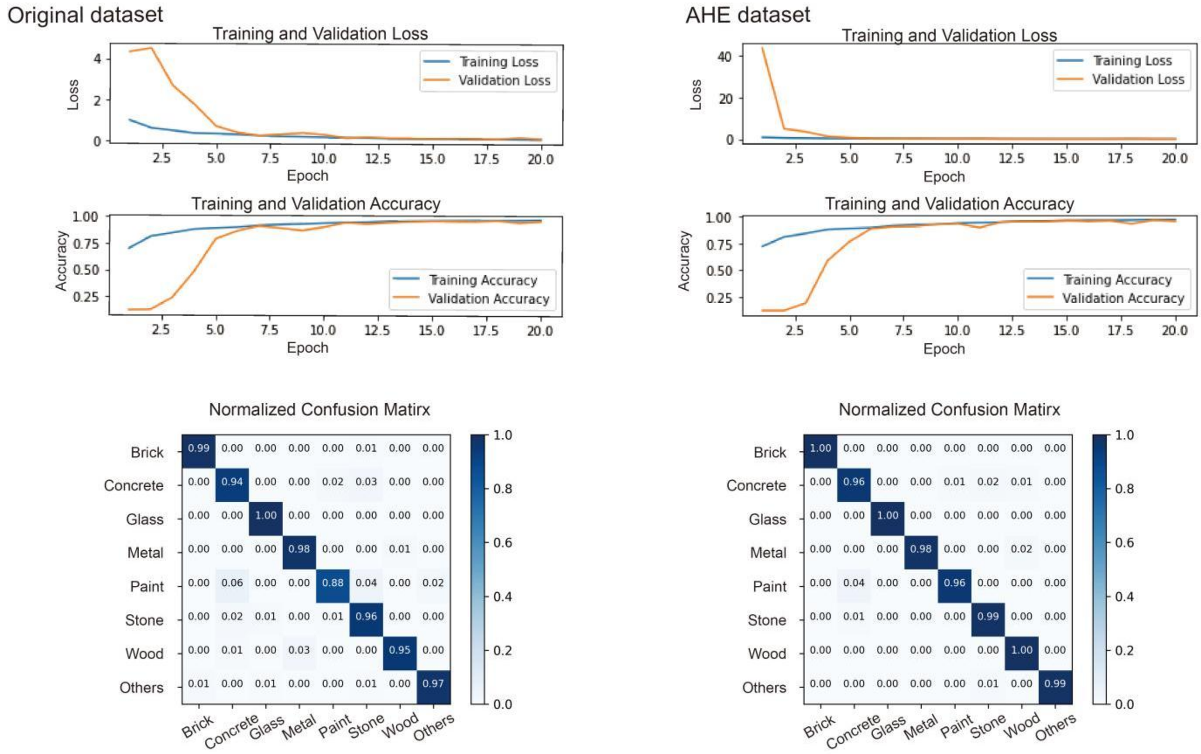

Figure 11. Comparison of loss and accuracy curves during training. Comparison of normalized confusion matrices.

Appendix V

Dataset	Accuracy	Precision	Recall	F1-score
Original	0.966	0.967	0.966	0.966
AHE	0.987	0.987	0.987	0.987

Table 1. Performance metrics comparison.