CAPTURING FAÇADE DIVERSITY IN URBAN SETTINGS USING AN AUTOMATED WINDOW TO WALL RATIO EXTRACTION AND DETECTION WORKFLOW

Nada Tarkhan
Massachusetts Institute of Technology
77 Massachusetts Avenue
Cambridge, MA, USA
ntarkhan@mit.edu

Samuel Letellier-Duchesne
Elementa Engineering (previously MIT)
54 W 40th St
New York, NY 10018, USA
duchesne@elementaengineering.com

Christoph Reinhart

Massachusetts Institute of Technology
77 Massachusetts Avenue
Cambridge, MA, USA
creinhart@mit.edu

ABSTRACT

Measuring window to wall ratios (WWRs) is key to assessing building performance as façade apertures control the admission of light, wind and heat. However, this data is not always publicly available. This paper details a methodology for automatically extracting and rectifying street-view facade imagery while utilizing a Machine Learning model to detect WWRs with architectural generalization in mind. Although several models of detection have emerged to categorize façade features, some lack robustness when presented with greater design diversity. Hence, the training and validation process of the Convolutional Neural Network (CNN) model utilized is centered around three main data categories; environmental conditions, design diversity and context. The results show that the proposed workflow sufficiently represents the WWRs of buildings in an area in Lisbon under varied design conditions. We find that the distribution of prediction accuracy, tested on 864 facades, shows that 72% of buildings are detected within the 10% error range.

Keywords: façade detection, window-to-wall ratios, computer vision, urban feature extraction

1 INTRODUCTION

Understanding diversity in urban environments is key to the assessment of cities and neighborhoods. With increasing densification of urban centers and the need to reduce global emissions, city-wide assessments and urban simulation models are becoming fundamental decision making tools that help shed light on current performance and inform strategies to pursue for future developments (Keirstead et al. 2010; Ang et al. 2020). Such models are typically used to evaluate energy consumption, daylight access, or indoor and outdoor thermal comfort. However the built environment is quite diverse and having access to detailed building characteristics is often a challenge in many cities.

To this end, the wider use of urban simulation tools demands increasingly detailed 3D models and greater accuracy of building properties, more representative of the specific urban context being studied. Advancements in computer vision workflows have allowed for more intricate detection and scene segmentation methods in urban image analysis. These algorithms are of particular importance in applications of façade feature extraction and the identification of key design elements in buildings. In addition to environmental studies, understanding architectural façade layouts has many uses that range from 3-D city model reconstruction, building anomaly detection and understanding prevalent architectural characteristics of a city's building stock and urban fabric (Bacharidis et al. 2020; Doersch et al. 2012; Gadde et al. 2016). The task of façade parsing has been tackled previously under multiple subject domains. In each application, a set of detection and data collection priorities are placed in line with the goals of the use-case. For instance, to serve the task of 3D building reconstruction, terrestrial and airborne laser scanning are the most frequently used technologies to obtain aerial photography that accurately capture building geometry (Kedzierski et al. 2015; Früh et al. 2003). While these workflows can be effective, they often rely on equipment which may not be readily available and require specific pre-processing and installation techniques. Street level imagery on the other hand provides a data source that is widely available and can be readily obtained in many cities around the world.

More specific to indoor analyses, WWRs are rarely available in building stock datasets and often rely on coarse assumptions. Existing approaches for this task have centered on two main workflows; the development of rule-based grammars for façade pattern recognition or detection models that employ a machine learning based approach (Cohen et al. 2014). The machine learning approaches utilize a set of training images which are typically annotated with the labeled features (eg. windows, doors etc.) and generate weights for use in predicting windows from urban images the models are presented with. In grammar-based methods, structural façade hierarchies and geometries are formulated to detect image compositions that operate under a set of rules and patterns (Mathias et al. 2016; Teboul et al. 2011). These guidelines are often hand-crafted and are derived from specific architectural typologies, belonging to a particular city, context or subset of buildings. While these models can be easier to implement because of the constrained solution space, they often fail to generalize to a wider set of design characteristics and architectures.

The relevance of extracting WWRs for environmental studies has previously been demonstrated in existing literature (Dogan et al. 2018). In a study that investigated daylight access and energy consumption in measured versus assumed WWRs in Chicago, it was found that the total daylight area was underestimated when a uniform 40% was utilized per industry standards (Szcześniak et al. 2022). The wider use of such detection models must focus on two points; the integration into a streamlined pipeline that facilitates usage and the integration of diversity-accounting metrics and evaluations during the conceptualization of the detection models. This paper proposes a window detection workflow that utilizes GIS datasets to extract facades of interest and utilizes a CNN-based model to extract WWRs. In addition to this, a qualitative 10-point assessment list is built into the evaluation criteria for detection, so that the model may generalize effectively to other cities and contexts with varying architectural styles. It is our ultimate goal to match the utilized method with the application on building performance simulations to be able tune detection models to cater to the input data image format and generalize to more diverse conditions.

2 METHODOLOGY

The proposed pipeline consists of 3 main steps, each with a separate task depending on the image processing task at hand. On a high level, we first start with image extraction which captures the individual urban facades to be analyzed. We then feed these images into a CNN detection model and get a labelled output with window annotations. The training and evaluation process of the CNN model are highlighted in the sections below. Finally, the results are post-processed using a developed script to extract the aggregate WWRs of each building. These steps are detailed further below and are summarized in Figure 2.

2.1 Image Extraction and Rectification

In order to first identify the buildings that will be surveyed, a Geo-DataFrame is inputted which stores the building polygon footprints and other building attributes such as height, building ID and construction details. For a particular context, this data can be sourced from platforms such as OpenStreetMap (Haklay et al. 2008) in shape file format which is a geospatial vector data format for GIS software, developed by ESRI (ESRI, 1998). The algorithm works by first identifying facades of interest through utilizing a concave hull algorithm or alpha shape; (Moreira et al. 2007) to capture the smallest concave area enclosing the building polygons within a desired city block. We tune the alpha parameter as it controls the extent of Delaunay triangulation, effectively resulting in different polygon enclosures around the building vertices. An example of how this algorithm works is represented below in Figure 1:

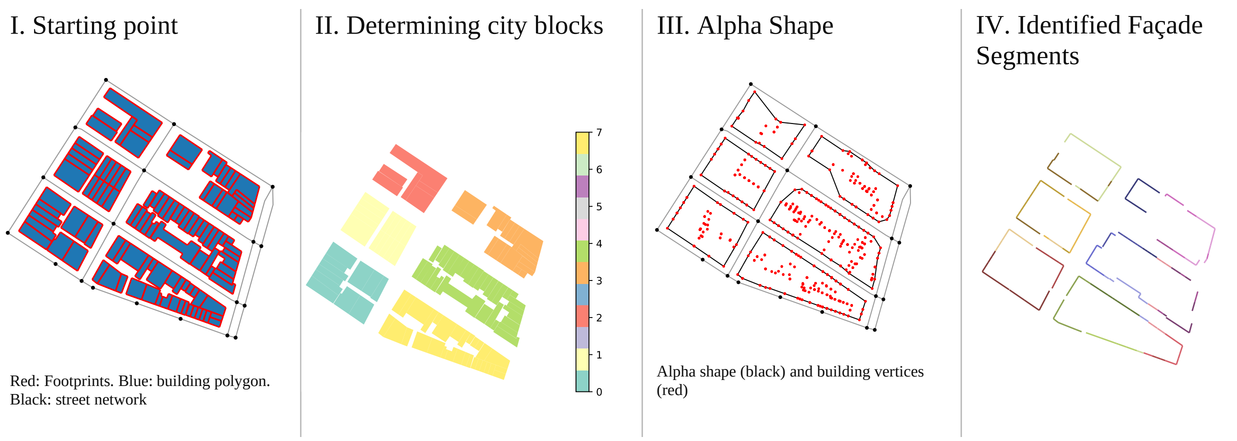


Figure 1. Representation of Alpha shape utilization in city blocks to determine façade segments

Secondly, the camera closest to a building facade is obtained through a metadata query of the Google Street View API using the coordinates of the center point of the façade which was computed using the centroid of the chosen façade segments (4th step above) using the two edge locations of the building. Thirdly, the pitch and FoV (Field of View) settings are adjusted to capture the desired central view of the façade up to a maximum of 120 degrees (as set by the Street View API) (Google 2012). To achieve this, the FoV is computed by first identifying the two façade vertices then calculating the camera angle based on the midpoint between the two points describing the façade extent and the camera location- this is shown in equation 1 where v1 and v2 represent the two corner vertices. The output in radians is then converted to degrees.

$$FoV_{Facade} = cos^{-1}((v1.v2)/(\left|\left|v1\right|\right|_2.\left|\left|v2\right|\right|_2 \qquad (1)$$

Finally, image extraction is then carried out through a second query of the Google Street View API using the actual camera location and the computed bearing angle to the facade. The image search output is set to "outdoors" so as not to obtain any interior building views. The Geotagged extracted images are stored in a Geo-package and displayed in their respective locations in QGIS (QGIS.org 2021) along with their referenced camera nodes for validation. Figure 2 shows how the façade images would be visualized and inspected before utilization.

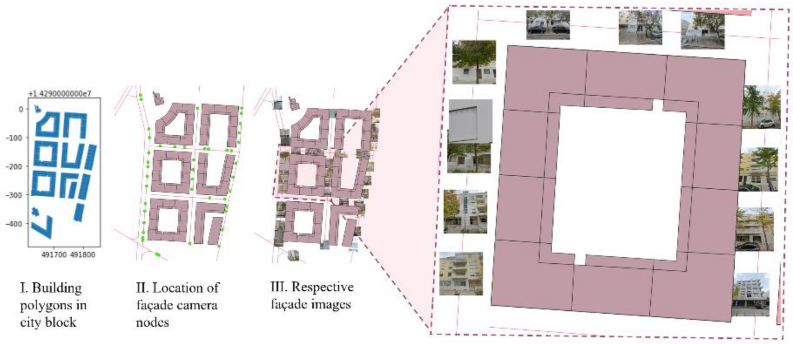


Figure 2. Steps for image extraction showing façade center point identification and image extraction

To automatically rectify the extracted images and transform them into orthogonal view, a homography calculation, which is essentially a geometric transformation describing a translation between two images of the same scene, is carried out on the dominant edges using a method that computes the vanishing point gradients in every façade image (Chaudhury et al., 2014). This step significantly improves detection accuracy as it eliminates skewed angles in upper floors. The dominant outer edges of the façade are then cropped and are used to define the visible wall area for the WWR calculation. With reference to translations from image space into pixel space, we extract all images at 640x640 pixel size to ensure consistency across the dataset.

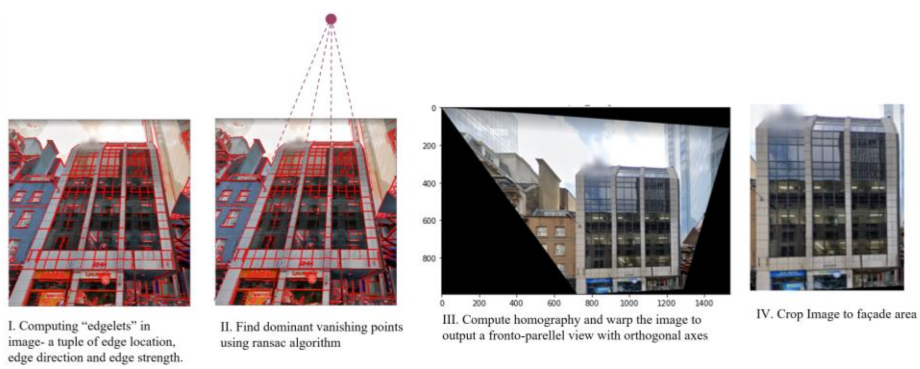


Figure 3. Steps for Orthogonal Transformation

2.2 CNN Model Training

The model utilized is a Convolutional Neural Network (CNN) based workflow that uses heatmaps to identify window key-points and groups them to form discrete window geometries using center verification (Li et al., 2020). The advantage of utilizing this method is that it simplifies the detection problem by assuming that window geometries can be described by four corner vertices, that can then be grouped into respective window polygons. Once the four points are detected, center verification is then carried out using Non-maximum-suppression for grouping of windows and geometry validation. The loss function utilized is an L2 loss function as shown below:

$$L = \frac{1}{k} \Sigma \left|\left| ytrue - ypredicted \right|\right|^2 \tag{2}$$

We utilize this method to train a model with newly annotated images and introduce a set of heuristics to compute the WWR with the additional wall area previously calculated. In addition to this, the hyperparameters are tuned and the model is trained over a longer duration (increased number of epochs) while the loss is monitored, until it stabilizes. The tuned parameters also include modifying the learning rate, introducing additional data augmentation techniques and making sure that window geometries were grouped accurately (based on 4 key-points) based on the detected vertices. If this was not satisfied, the window geometry was excluded from the calculation and treated as invalid. The final model parameters and environment are summarized in the table below.

Table 1: Description of CNN Method Utilized

Architecture	• Keypoint positions are extracted by performing non-maximum suppression (NMS) • Distances between vertices are calculated and used to group windows • L2 Loss is utilized to evaluate error
Evaluation Metrics	• ResNet18 • IOU (Intersection over Union), Precision, Recall Scores
Model Parameters	• Optimizer: Adam • Learning Rate: initial at 10-3 , then stepped down to 10-4 • Data Augmentation: Random Horizontal flipping, random scaling, random color jittering (adjusting the brightness, saturation and contrast)

The training process relied on annotated façade datasets that were both manually labelled and sourced from publicly available datasets. The public datasets included; TSG-20○2 , TSG-60○3 , ZuBuD○4 , CMP and ECP(Tyleček et al., 2013). Although rich in design diversity, these datasets are quite different from views typically obtained from street view imagery which have a wider variety in quality and resolution, viewing angles and environmental obstructions (eg. trees, signage etc.). For this reason, additional labelled data of 537 images was produced using images obtained from street view platforms and was labelled using the labelme annotation tool (Russell et al., 2008). The total number of images that were used for model training and validation were 3955. After the model is trained on the expanded image dataset, it can then be utilized for inference on additional façade images obtained in various contexts. The post-processing steps involve the calculation of the areas enclosed by all windows detected and the wall edges (to form a polygon) to calculate the WWR, as shown below in equation 3. This data is then outputted per building ID in a CSV file . The sequence of this workflow is summarized in Figure 4.

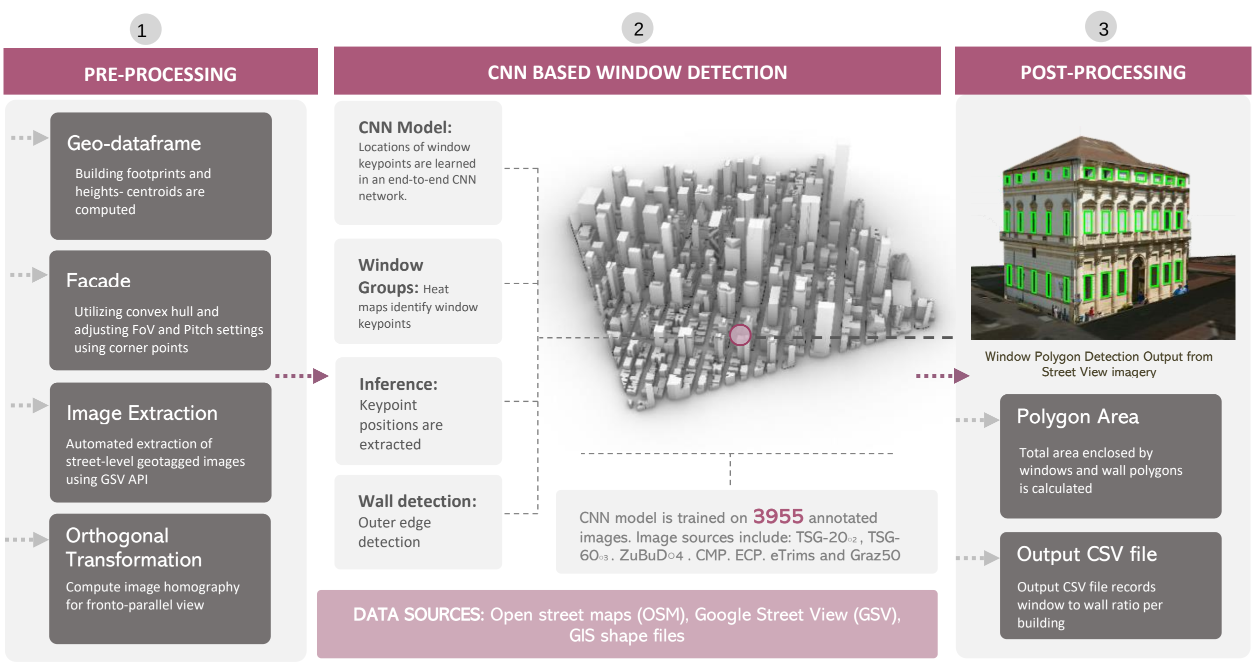


Figure 4. Summary of Proposed Pipeline

$$WWR = \frac{\sum Area\ of\ windows}{Area\ of\ Wall} \tag{3}$$

2.3 CNN Model Evaluation Metrics

To evaluate the CNN model performance, a few conditions are observed visually and quantitative metrics are used to calculate derived error ranges of prediction. These methods are summarized below.

2.3.1 Qualitative Criteria

Since the primary goal is to capture design diversity, we look at specific conditions that represent design variations that are commonly found in several urban context but may be difficult to capture. A tick mark symbolizes that this condition or design variance is successfully captured in most of the cases. The notes added indicate where the model needed to be fine-tuned during the training process to enhance the detection in this condition.

Table 2: Qualitative Assessment Metrics

	Qualitative Scoring Criteria	**Method performance evaluation**
1	Non-uniform window alignment	✓
2	Non-uniform Window geometry	Arched forms detected as orthogonal
3	Multi-material facades	✓
4	Textures and patterns	✓
5	Lighting conditions and shadow occlusions	✓
6	Fully Glazed Facades	Additional training data required to improve detection in this condition
7	Façade obstruction elements (balconies, staircases)	✓
8	Distinction between doors and windows	✓
9	Densely populated facades (many small windows)	Additional training data required to improve detection in this condition
10	Depth perception (inset windows)	✓

Given the above initial assessment, we gear the training and testing process towards enhancing detection in the categories above which are considered more challenging to detect. This validation step is only focused on detection accuracy of the window geometries. To simplify this process, the images used for model validation and testing focused on the following categories:

- *Environment:* This includes diversity in lighting conditions, shadows as well as lower resolution images.
- *Context:* For this specific application, we feed the model additional images from various cities including New York, London, Paris and Lisbon. Lisbon is largely represented due to the interest in applying this workflow there for a validation case study.
- *Design:* Includes a wider set of design conditions that encompass small dense windows, fully glazed facades and large façade areas.

Table 3: Training and Validation dataset size per category

	Category	**Validation data set size**
1	Environment	395
2	Context	395
3	Design	395

2.3.2 Quantitative Scores

To evaluate the quantitative performance of the models against different training cycles, the IoU (Intersection over Union) metric was utilized. This metric is a ratio between the area encompassed between the predicted area and ground truth, over the combined area of prediction and ground truth. The metric rewards a higher overlap area against the actual window locations and hence gives an indication of prediction accuracy.

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \tag{4}$$

In addition to this, the precision and recall scores are also utilized which are measures that quantify classification quality by calculating the differences between true positives and false negatives.

2.4 Case Study Area: Lisbon Parishes

In order to test and validate the window detection model, an area in Lisbon was used as a case study. This test area was composed of three parishes that included Beato, Marvilla and Parque des Nacoes. The validation process had 2 main steps. The first step involved manually measuring the window to wall ratio from street view imagery with respective building IDs and geolocation identified. The second step was using the same building IDs to detect the window to wall ratio using the CNN model. In this way, we can compare the percentage error and deviation from the manual measurements. The dataset included a representation of the building typologies in each parish and sampled an approximate building number that was representative of parish size. A total of 864 facades were surveyed.

Figure 5. Lisbon Study Area- 3 parishes

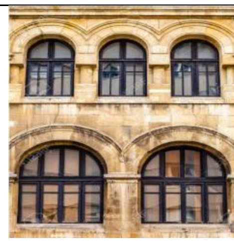
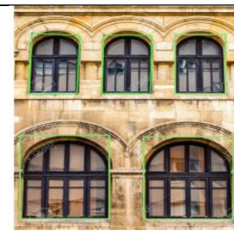
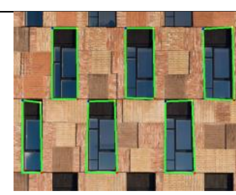
The manual surveying of the buildings was also conducted using Google street view images such as to utilize the same data source as the CNN detection process. The orthogonal correction was carried out manually and the WWRs were calculated from a typical window layout on a sample floor. If the façade showed a wide variation across floors, all windows were manually surveyed in that facade. Similar to how invalid images were treated in the automated workflow, if occlusions were present (trees, distortions, large distance from camera etc.), then the images were not annotated and were invalid for use. All manually annotated images were inspected closely to make sure the annotations were correct.

3 RESULTS

3.1 Assessment Conditions: Qualitative Assessment

The below images represent some of the conditions noted in table 1. A selection of design conditions were tested out using the newly trained CNN model. The visual results indicate that the algorithm detection is successful in detecting windows against these conditions. The output images with the output bounding geometry representations for the windows are shown below using the updated trained model.

Table 4: Visual Results

Design Condition	**Input Image**	**Output Image with Detection**
Irregular Window Sizes		
Façade Occlusions (Vegetation and balconies)		
Façade Textures		
Non-Axially aligned windows (irregular grid) *Example 1*		
Example 2		

3.2 Quantitative Assessment

The results below represent the difference between the first CNN model utilized, with only public image datasets (old) and the newly trained model with additional labelled images inputted and tuned hyperparameters (new). The results below show the performance on the batch images that were tested in the three categories highlighted below along with the increase in IoU scores on the same tested images.

The biggest detection accuracy increase can be seen in the context category, representing a 9.5% increase in IoU sores. The smallest performance increase can be seen in the environment category. This could be attributed to the already high IoU scores in this category.

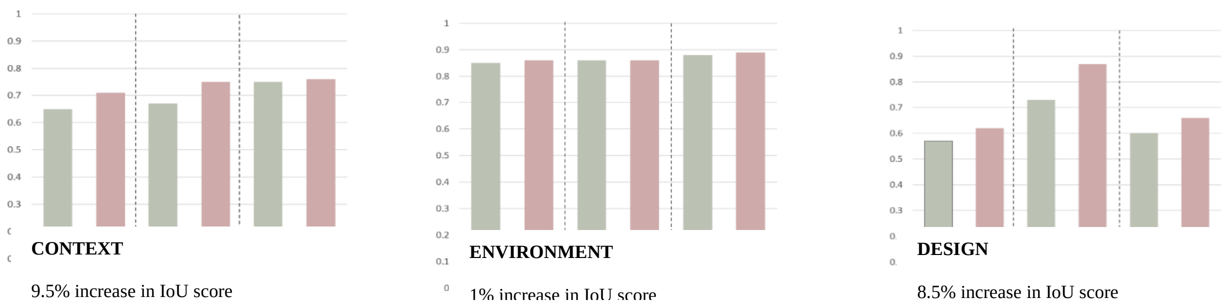


Figure 6. Detection Scores for different Data categories

3.3 Lisbon Results

The results below show the differences between the detected window to wall ratios and the manually surveyed ones. A few insights can be made with regards to the overall accuracy as well as the sensitivity in detection across the different window typologies.

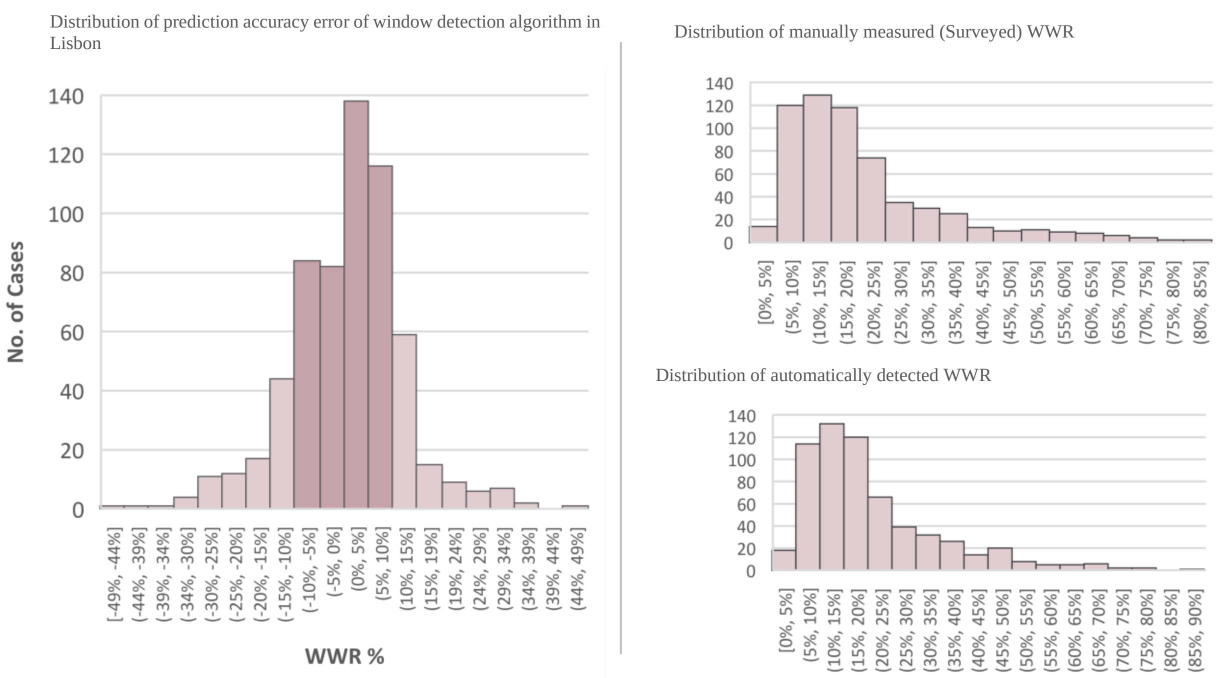


Figure 7. Validation of detection against manually measured images

The distribution of prediction accuracy error of the window detection algorithm tested on 864 facades of buildings in Lisbon shows that 72% of buildings are detected within 10% error range. With reference to window typology, punched windows have the highest detection accuracy while fully glazed facades (with WWRs between 70-90%) have the lowest accuracy range.

4 DISCUSSION

The workflow detailed in this paper outlines a WWR extraction pipeline in diverse urban environments. The results show that the method can sufficiently detect windows in more challenging façade conditions and design configurations. The ultimate goal is to help enhance urban level model resolutions and generate models that can make predictions with higher confidence levels.

Although effective, the detection model is largely dependent on the quality of the images obtained from the street view imagery. As noted earlier, these images are often times noisy and have several obstructions that may likely decrease detection quality, as resolutions are not standardized across the platforms that typically provide this urban street view data. In addition to the quality of input data, further heuristics may need to be embedded to further enhance detection in fully glazed facades as this represents the most challenging condition. Other expansion avenues could include the use of emerging methods such as Polygon RNN (Castrejón et al. 2017) that would allow for both area extraction and bounding geometry detection.

Moreover, this workflow is limited to façades that are only accessible through Google Street View imagery or other platforms that provide publicly available urban images of buildings. Meaning that images of facades captured in alley-ways (with no vehicular access) and courtyards within buildings would be difficult to obtain. One possible solution for this is to utilize an urban imagery crowd-sourced database such as Mapillary (Neuhold et al., 2017) where it may be possible for people to upload images of otherwise inaccessible portions of the building. Another limitation of this workflow is in capturing complex façade outlines. As it stands, this method works best with mostly orthogonal wall edges- more elaborate façade forms may require additional model pre-processing.

Finally, this method reflects on both the training and evaluation process for generating more generalizable façade detection models, specifically geared towards capturing WWRs with urban simulation applications in mind. Approaching urban feature detection with sensitivity towards diversity in mind is essential to their application on a wider set of uses. The reproducibility of the results are hence a function of both the image extraction method as well as the detection algorithm which were tested in this paper in Lisbon. While the paper introduces the three categories of environment, context and design for more targeted model training and evaluation, expansions to different contexts and architectural styles are possible through even wider training sets. This expandability provides a notable advantage over more rigid rule-based façade parsing approaches that have typically been used to extract window geometries in façade studies.

5 CONCLUSION

This paper presents an automated extraction workflow that performs combined image extraction and rectification, utilizes the state of the art CNN architecture for window detection and finally computes the resultant WWR of urban facades. In the case study applied in Lisbon, the results show that for 72% of investigated facades WWRs were within the 10% error range from manually annotated images. The identification of window typologies showed that punched windows have the highest detection accuracy while fully glazed facades have the lowest. This can be largely attributed to high reflectance and color variations present in images with larger glazing areas. The paper also proposes a systematic way to evaluate the performance of detection models with the consideration of design diversity and the application into building performance studies as the primary use-case. The method highlighted in this paper also emphasizes the performance gains attributed to approaching the training and validation process with a categorical batch training procedure that facilitates the model evaluation. Further applications of this pipeline could assess WWRs in different global cities and test correlations with other building attributes (such as building age, constructions, etc.).

REFERENCES

Ang, Y. Q., Z. M. Barzillai, and C. F. Reinhart. 2020. From Concept to Application: A Review of Use Cases in Urban Building Energy Modeling, *Applied Energy*, vol. 279, p. 115738. DOI: 10.1016/j.apenergy.2020.115738

Bacharidis, K., F. Sarri, and L. Ragia. 2020. 3D Building Façade Reconstruction Using Deep Learning, *ISPRS International Journal of Geo-Information*, vol. 9(5), p. 322. DOI: 10.3390/ijgi9050322

Castrejón, L., K. Kundu, R. Urtasun, and S. Fidler. Annotating Object Instances with a Polygon-RNN, *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition*, *CVPR 2017*, pp. 5230-5238.

Chaudhury, K., S. Diverdi, and S. Ioffe. 2014. Auto-Rectification of User Photos, *2014 IEEE International Conference on Image Processing, ICIP*, pp. 3479-3483.

Cohen, A., A. G. Schwing, and M. Pollefeys, 2014. Efficient Structured Parsing of Facades Using Dynamic Programming, *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 3206-3213.

Doersch, C., S. Singh, A. Gupta, J. Sivic, and A. A. Efros. 2012. What Makes Paris Look like Paris?, *ACM Transactions on Graphics*, vol. 31, no. 4. DOI: 10.1145/2185520.2185597

Dogan, T. and M. Knutins. 2018. Cityseek: Towards Urban Daylight Models Based on Gis Data and Semi-Automated Image Processing, *Simulation Series*, vol. 50(7), pp. 1-8.

ESRI, 1998. ESRI Shapefile Technical Description, *Computational Statistics*, vol. 16. DOI: 10.1016/0167-9473(93)90138-J

Früh, C. and A. Zakhor. 2003. Constructing 3D City Models by Merging Aerial and Ground Views, *IEEE Computer Graphics and Applications*, vol. 23(6), pp. 52-61.

Gadde, R., R. Marlet, and N. Paragios. 2012. Learning Grammars for Architecture-Specific Facade Parsing, *International Journal of Computer Vision*, vol. 117(3), pp. 290-316. DOI: 10.1007/s11263-016-0887-4

Google, Google Street View Image API, 2012, *Google*.

Haklay, M. and P. Weber. 2008. OpenStreetMap: User-Generated Street Maps. Pervasive Computing, *IEEE Pervasive Computing*, vol. 7(4), pp. 12-18.

Kedzierski, M. and A. Fryskowska, 2015. Methods of Laser Scanning Point Clouds Integration in Precise 3D Building Modelling, *Measurement: Journal of the International Measurement Confederation*, vol. 74, pp. 221-232. DOI: 10.1016/j.measurement.2015.07.015

Keirstead, J., N. Samsatli, and N. Shah. 2010. *SynCity: An Integrated Tool Kit for Urban Energy Systems Modelling*, *Energy Efficient Cities: Assessment Tools and Benchmarking Practices*, 21.

Li, C. K., H. X. Zhang, J. X. Liu, Y. Q. Zhang, S. C. Zou, and Y. T. Fang, 2020. Window Detection in Facades Using Heatmap Fusion, *Journal of Computer Science and Technology*, vol. 35(4), pp. 900-912. DOI: 10.1007/s11390-020-0253-4

Mathias, M., A. Martinović, and L. Van Gool. 2016. ATLAS: A Three-Layered Approach to Facade Parsing, *International Journal of Computer Vision*, vol. 118(1), pp. 22-48. DOI: 10.1007/s11263-015-0868-z

Moreira, A. and M. Y. Santos. 2007. Concave Hull: A Jt-Nearest Neighbours Approach for the Computation of the Region Occupied by a Set of Points, *GRAPP 2007 - 2nd International Conference on Computer Graphics Theory and Applications, Proceedings*, vol. GM, no. R/-.

Neuhold, G., T. Ollmann, S. R. Bulo, and P. Kontschieder. 2017. The Mapillary Vistas Dataset for Semantic Understanding of Street Scenes, *Proceedings of the IEEE International Conference on Computer Vision*, vol. 2017-October, pp. 4990-4999.

QGIS.org, QGIS Geographic Information System. QGIS Association, Open Source Geospatial Foundation Project, 2021.

Russell, B. C., A. Torralba, K. P. Murphy, and W. T. Freeman. 2008. LabelMe: A Database and Web-Based Tool for Image Annotation, *International Journal of Computer Vision*, vol. 77, no. 1–3. DOI: 10.1007/s11263-007-0090-8

Szcześniak, J. T., Y. Q. Ang, S. Letellier-Duchesne, and C. F. Reinhart. 2022. A Method for Using Street View Imagery to Auto-Extract Window-to-Wall Ratios and Its Relevance for Urban-Level Daylighting and Energy Simulations, *Building and Environment*, vol. 207, p. 108108. DOI: 10.1016/j.buildenv.2021.108108

Teboul, O., I. Kokkinos, L. Simon, P. Koutsourakis, and N. Paragios. 2011. Shape Grammar Parsing via Reinforcement Learning, *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR2011*, pp. 2273-2280.

Tyleček, R. and R. Šára, 2013. Spatial Pattern Templates for Recognition of Objects with Regular Structure, *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 8142 LNCS, pp. 364-374.

AUTHOR BIOGRAPHIES

NADA TARKHAN (ntarkhan@mit.edu) is a PhD candidate in the Building Technology group at the MIT architecture department. She holds a Masters in Design Studies (MDes) in Energy and Environments from the Harvard Graduate School of Design. Her research interests lie in the assessment and detection of urban features as they relate to indoor heat resiliency and climate readiness. Nada previously worked as a Sustainability Consultant at Arup, where she engaged with various building physics analyses and simulation workflows.

SAMUEL LETELLIER-DUCHESNE (duchesne@elementaengineering.com) is a building scientist and computational scientist working at Elementa Engineering, DPC. He transitioned from academia to the industry to pursue his interest in accelerating the decarbonization of the built environment. He holds a PhD in mechanical engineering from Polytechnique Montréal.

CHRISTOPH REINHART (creinhart@mit.edu) is a professor and the director of the Building Technology Program at the MIT Architecture Department. He is a building scientist and architectural educator working in the field of sustainable building design and environmental modeling. At MIT he is leading the Sustainable Design Lab (SDL), an inter-disciplinary group with a grounding in architecture that develops design workflows, planning tools and metrics to evaluate the environmental performance of buildings and neighborhoods.