[Image-based prediction of residential building attributes with deep learning](https://doi.org/10.1111/jiec.13591)

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Summary

Cities rely on accurate building data for effective planning and to understand how resources are used. This includes analyzing both embodied greenhouse gas emissions and identifying potential locations for infill development. However, collecting reliable information on attributes like building size or age is challenging, as traditional surveys are costly to conduct, difficult to maintain, have uneven availability across regions, and often contain highly uncertain data.

This research estimates building attributes—floor area and age—using one-shot image-based machine learning on Google Street View images. We demonstrate the performance of our model in Toronto and five other Canadian cities, highlighting the model's effectiveness in different urban contexts and the advantages of local training data. We use the EfficientNetV2 model and nearly 100,000 building images and real estate transactions from Toronto, Canada, to train and evaluate our prediction model.

Key Takeaways:

1) Our model predicted building floor area with a mean error of 19%, and predicted building age with an accuracy of 70% for buildings in Toronto (see Figure 1 for example predictions). This task had not been previously attempted using single street-view images. Our approach reduces computational complexity and processing time, making it easier to implement and scale for large datasets.

2) Our model predicts internal floor area, which isn’t directly visible from the outside. This ability to predict unseen features based on external images highlights the power of deep learning to infer hidden building attributes, thus opening new avenues for urban analysis and planning.

3) Generalizing models across diverse urban landscapes is a challenging task, since different architectural styles and building age distributions vary significantly across cities, highlighting the importance of using at least some local training data.

4) Age identification is challenged by the chimera nature of buildings; as buildings are repaired and renovated, it becomes both philosophically and technically harder to specify a specific age.

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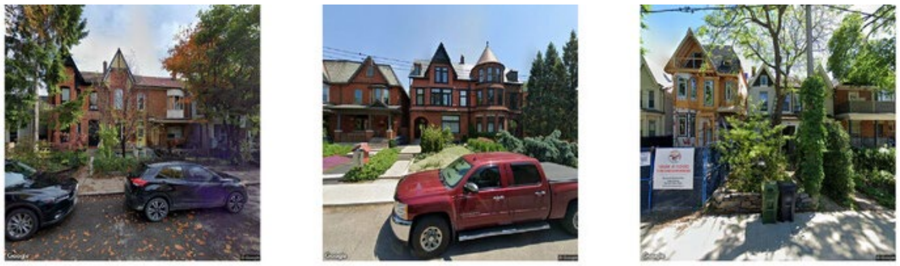
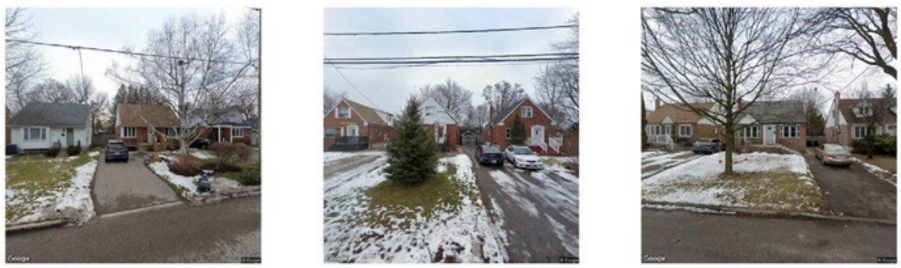
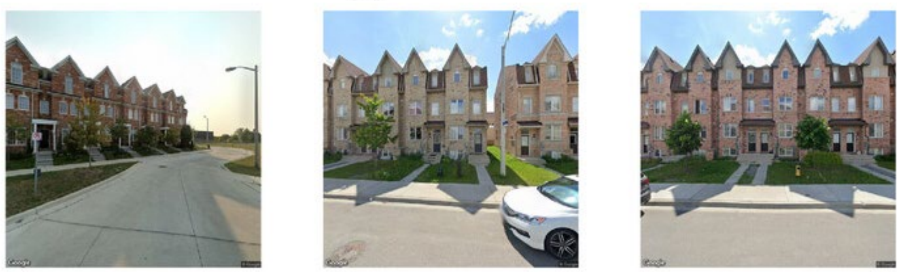


(a) pre-1920



(c) 1940-1960



(f) post-2000

Figure 1: *Examples of buildings with correct age predictions for selected age classes.*

Table 1. *Test performance for age and area prediction across selected cities. Lower values are better for MAPE; higher values are better for accuracy metrics.*

City	Age Prediction		Area Prediction
	Accuracy (%)	Off-by-One Accuracy (%)	Mean Absolute Percentage Error (MAPE) (%)
Toronto	70	89	19.42%
Calgary	66	90	19.08%
Hamilton	40	62	19.45%
Moncton	46	81	23.10%
Montreal	36	60	27.12%
Victoria	41	72	34.67%

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