

# Image Scale Estimation Using Surface Textures for Quantitative Visual Inspection

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UNIVERSITY OF WATERLOO  
FACULTY OF ENGINEERING



Computer Vision for  
Smart Structure

# Background



## Background (Continue)

Routine visual inspection is mandated to identify and quantify structural defects.



# Recent Developments

Several image processing and computer vision techniques have enabled automatic detection of regions-of-interest (**ROIs**)

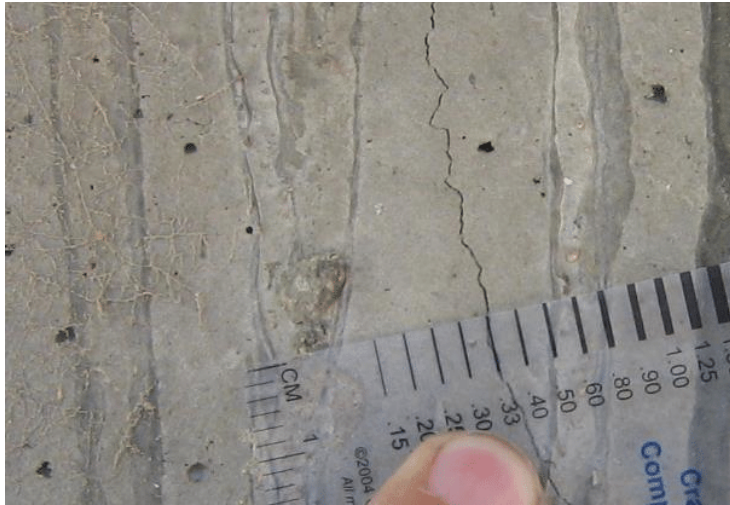


An et al. 2018



Hoskere et al. 2020

# Existing or Potential Approaches for Quantification



Ruler/marker-based measurement



Stereo camera



App-based measurement

# Is There an Easier Way to Make Physical Measurements?



**Scale?**

# Key Idea of the Proposed Technique



# Proposed Approach

## Objective

CNN-based image scale estimation framework which translate surface textures to an image scale (i.e. pixel/mm).

## Advantages

- Only require a single camera
- Can be applied to historical images
- One-time training of a CNN model
- Can be added to existing feature detection processes to enable end-to-end inspection algorithm

## Limitations

- Assumes image is taken parallel to the scene (to estimate a single scale).

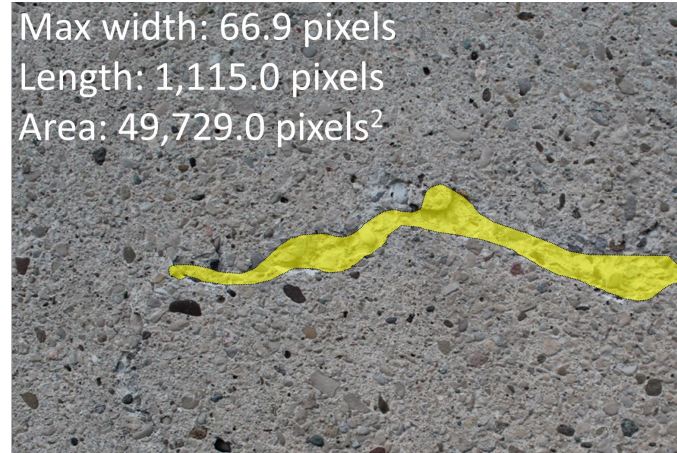


# How to Use the Proposed System

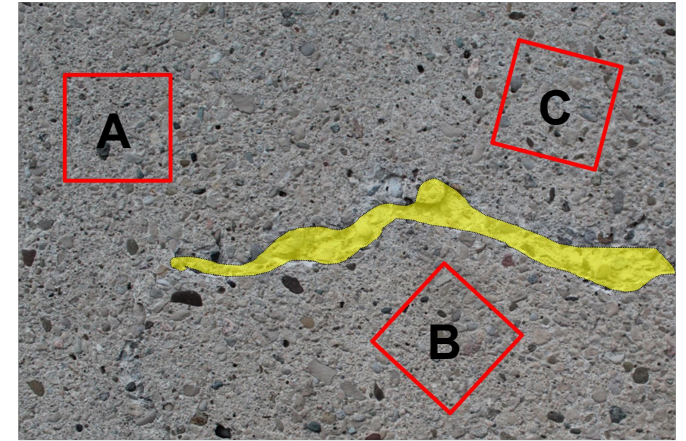
**Step 1.** Image collection for target region



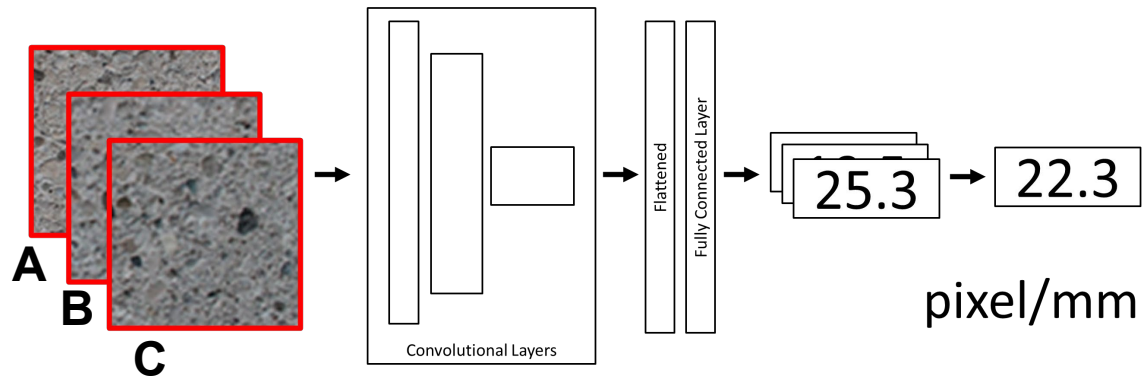
**Step 2.** Region-of-interest (ROI) detection



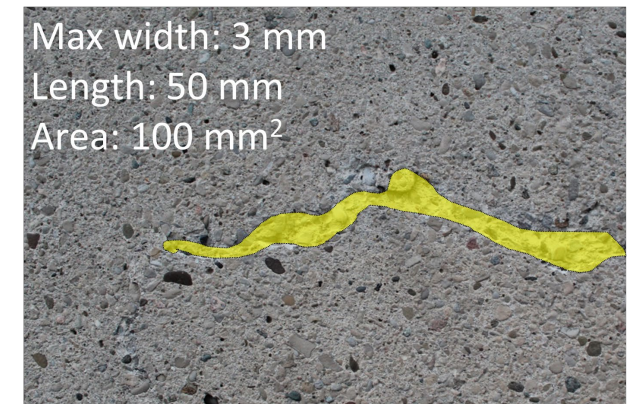
**Step 3.** Patch extraction of surface texture



**Step 4.** Image scale estimation using trained CNN model

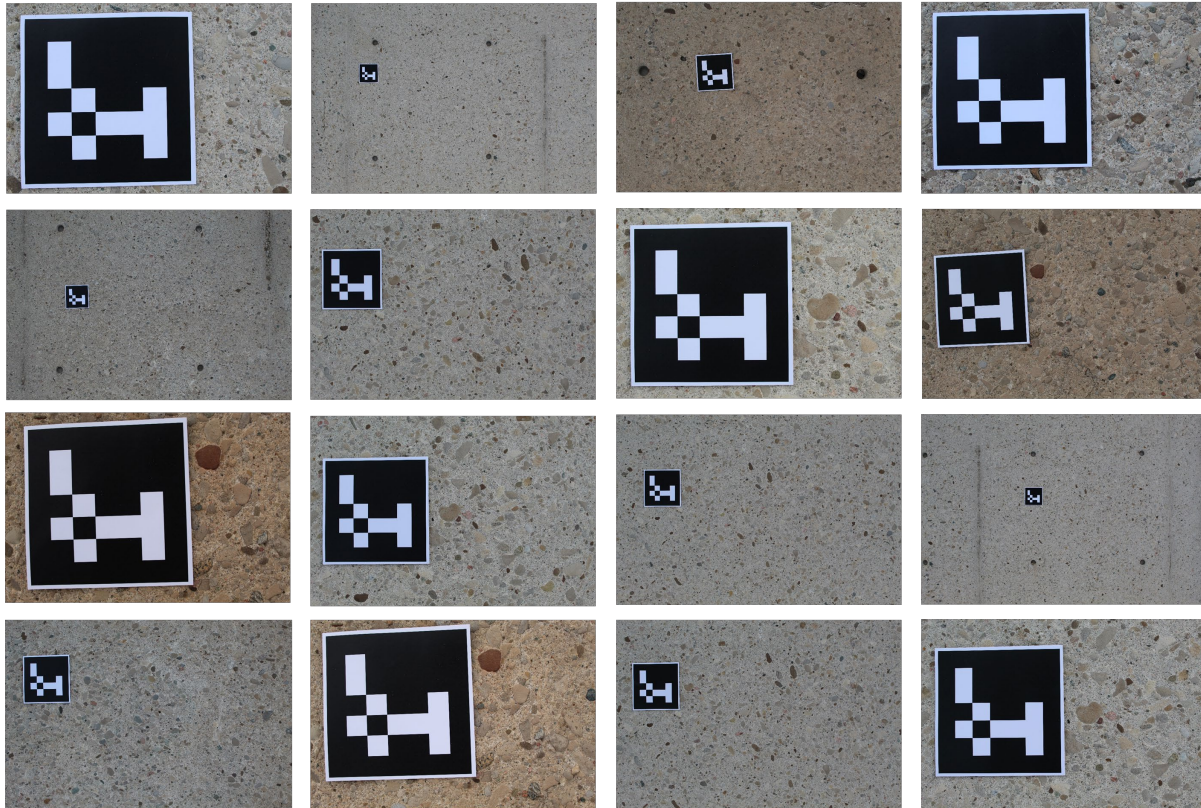


**Step 5.** Quantitative ROI evaluation

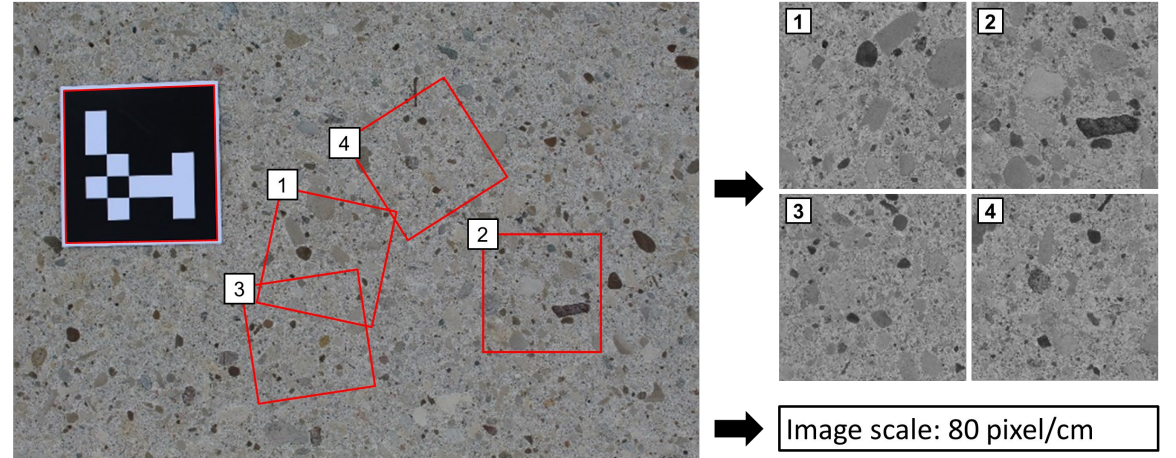


# One-time Training Phase

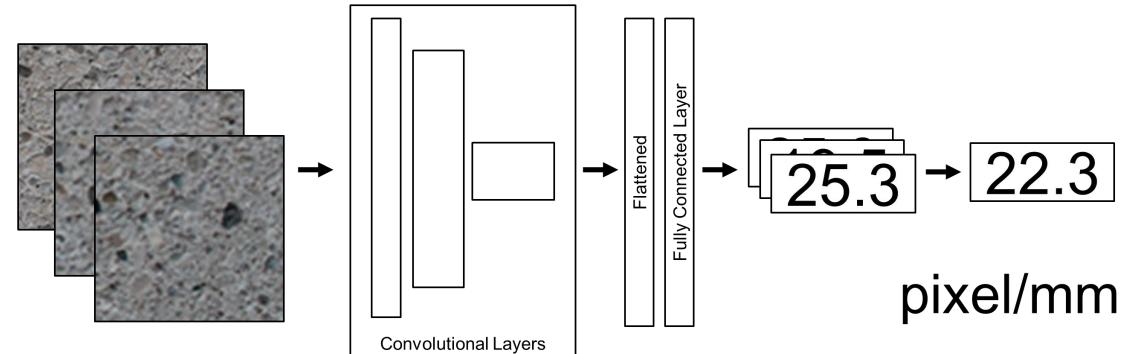
**Step 1.** Marker-included image collection for model training



**Step 2.** (For each image) Marker detection, scale calculation, and patch extraction



**Step 3.** CNN model training using patches and their corresponding image scales



**Note that this is the process to make ground-truth database and train the network.**

# Experimental Validation: Test Structures



Pedestrian Bridge  
(PED)

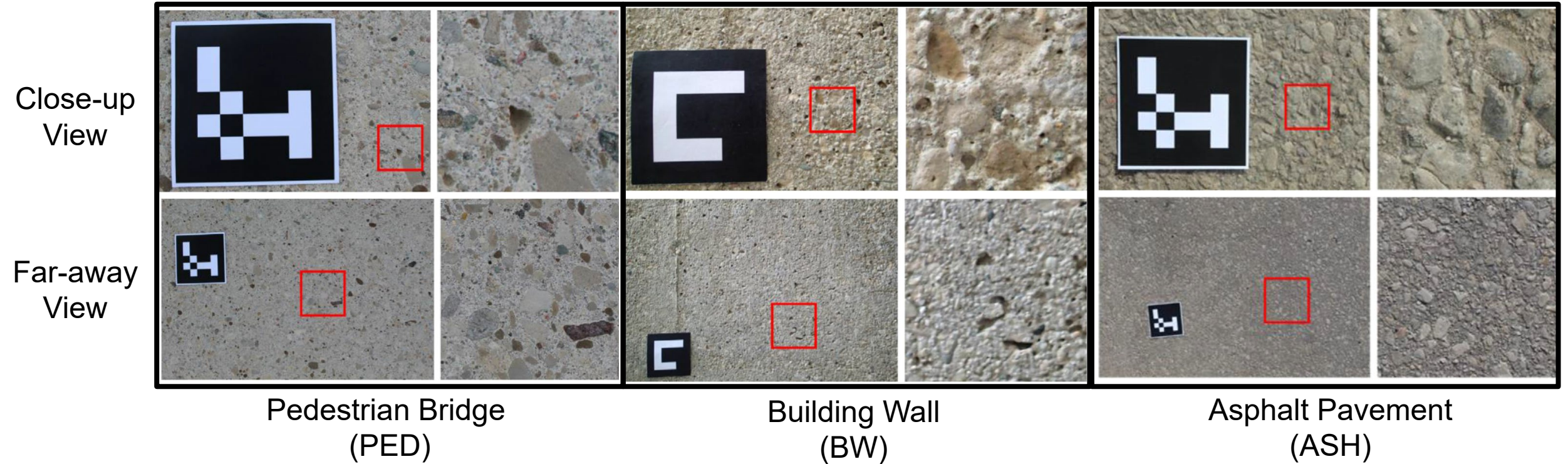


Building Wall  
(BW)

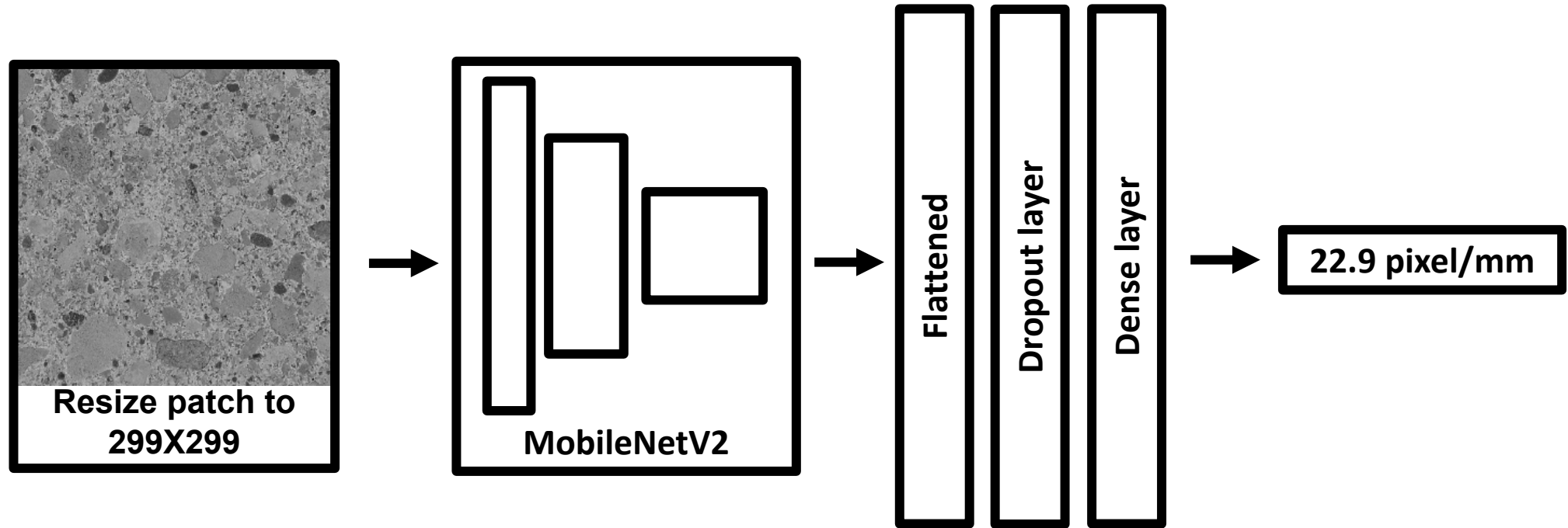


Asphalt Pavement  
(ASH)

# Surface Textures from PED, BW, and ASH



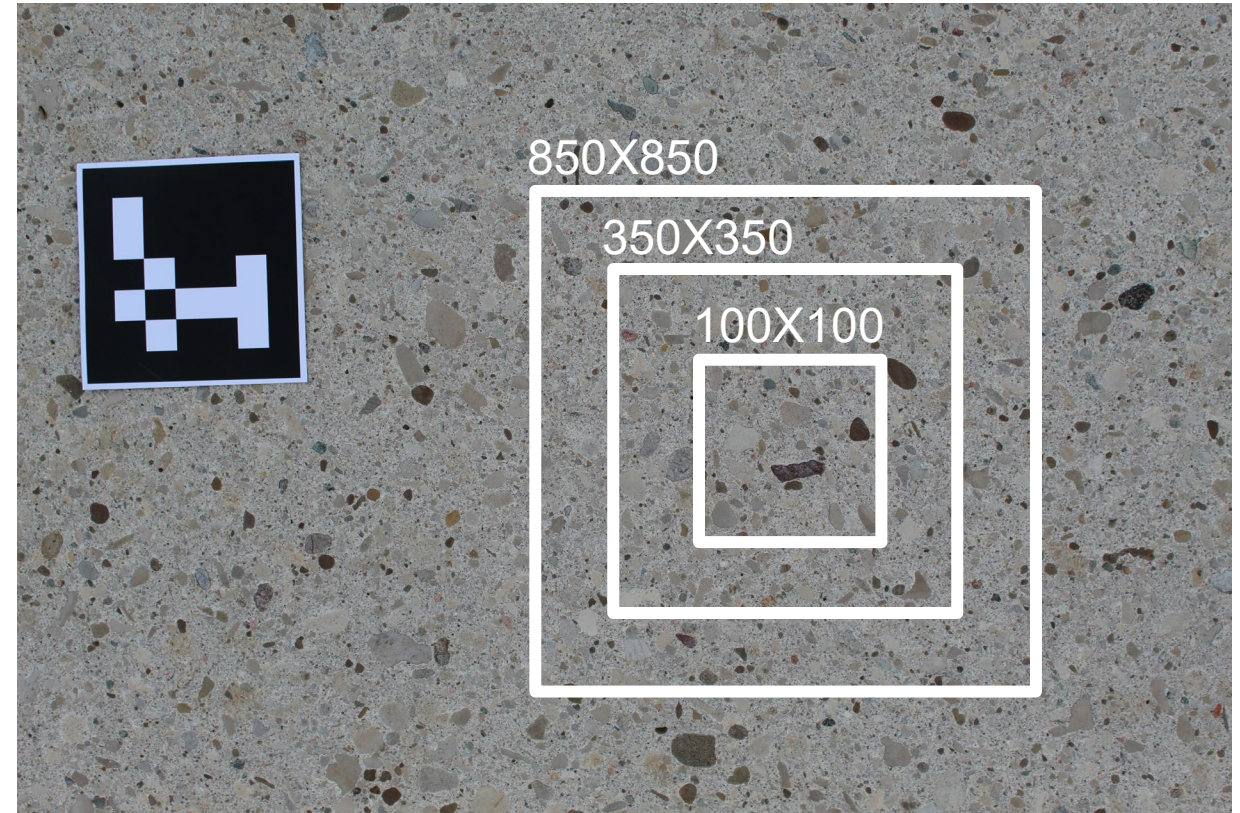
# Network Architecture and Loss Function



$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \frac{|y - \hat{y}|}{y}$$

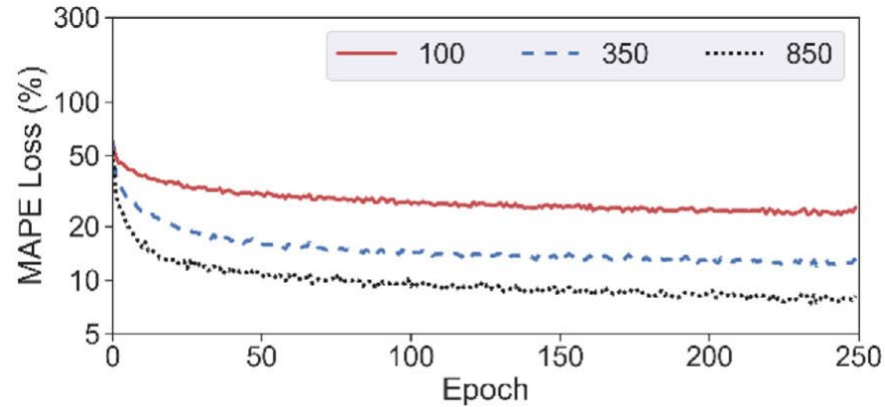
# Training Details

- SGD optimizer:
  - learning rate:  $10^{-4}$
  - decay: 0.9
  - momentum: 0.01
- Texture patch augmentations:
  - Horizontal and vertical flips
  - Minor Rotations
  - Brightness changes  $\pm 10\%$
- Patch sizes:
  - 100X100 pixels
  - 350X350 pixels
  - 850X850 pixels
- Extract  $\sim 50$  patches per image

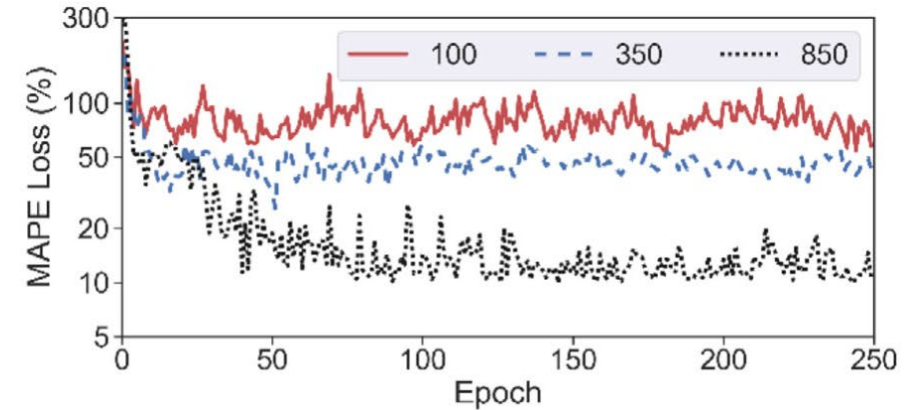


# Training Details (Continue)

Patch size training results (PED):



Training

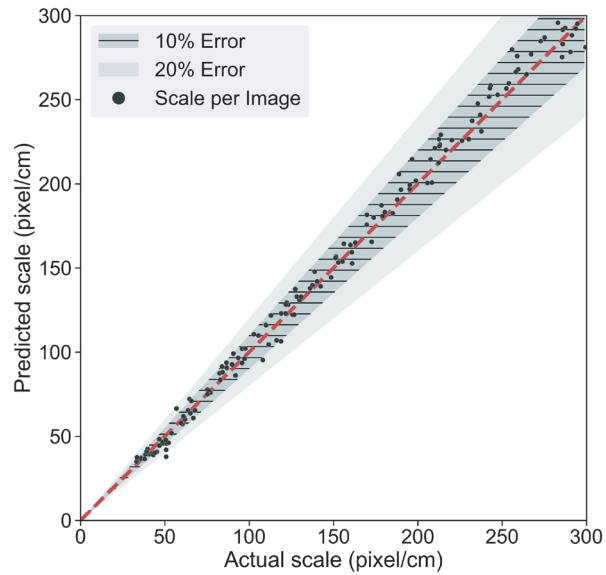


Testing

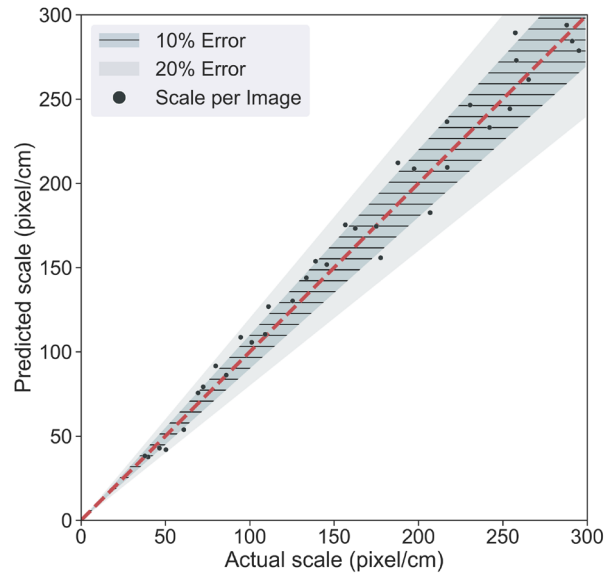
Final Training Dataset:  
(Using patch size 850X850 pixels)

Dataset	Total Number of Scenes (training/testing)	Total Number of Images (training/testing)
PED	22 (18/4)	191 (154/37)
BW	14 (12/2)	434 (352/82)
ASH	21 (17/4)	182 (149/33)

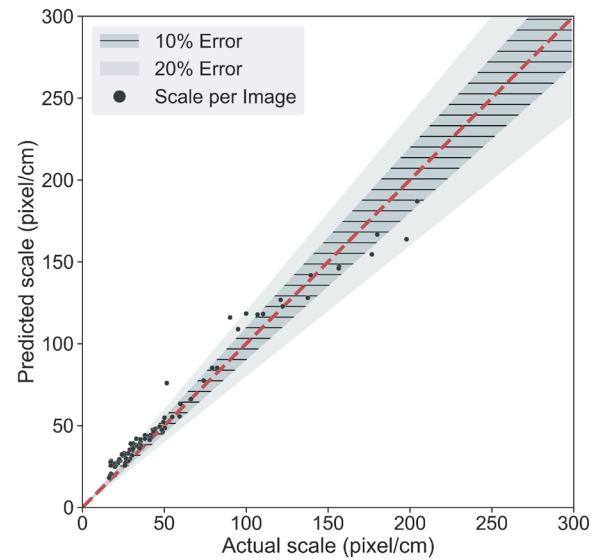
# Experiment Results (Scale Estimation)



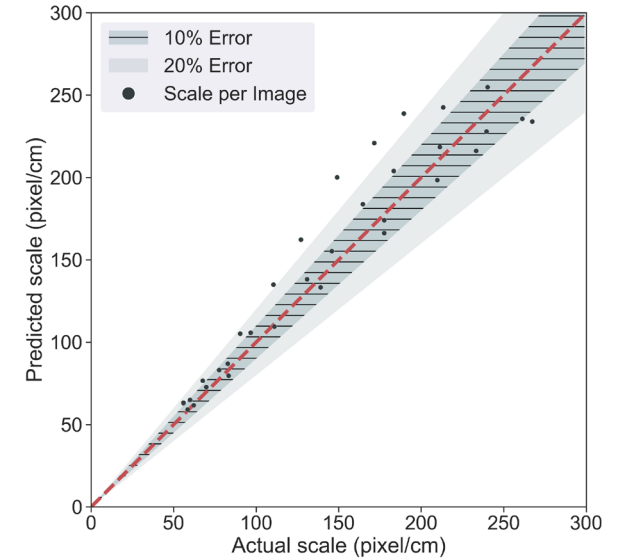
PED – Training



PED – Testing



BW – Testing



ASH – Testing

Validation Results:  
(avg. error  $\pm$  std. dev.)

Aggregation	PED	BW	ASH
Mean	6.7% $\pm$ 4.0%	15.8% $\pm$ 13.6%	10.5% $\pm$ 8.4%
Median	7.3% $\pm$ 4.5%	14.1% $\pm$ 11.9%	9.9% $\pm$ 8.3%



Thank you!

Any questions?

# References

## Image sources:

- <https://www.facebook.com/Analysis.and.design.of.concrete.Bridges/>
- <https://www.constructioncanada.net/older-masonry-buildings-benefits-risks-and-design-approaches-for-adding-interior-insulation/>
- [https://en.wikipedia.org/wiki/Asphalt\\_concrete](https://en.wikipedia.org/wiki/Asphalt_concrete)
- <https://www.dcpu1.com/blog/what-causes-concrete-to-crack/>
- [https://www.researchgate.net/publication/335446851\\_Challenges\\_of\\_preserving\\_modernist\\_concrete](https://www.researchgate.net/publication/335446851_Challenges_of_preserving_modernist_concrete)
- [https://www.researchgate.net/profile/Seda\\_Oezdemir2/publication/307204713/figure/fig3/AS:400421664378881@1472479372061/Measured-crack-width-allowing-water-infiltration.png](https://www.researchgate.net/profile/Seda_Oezdemir2/publication/307204713/figure/fig3/AS:400421664378881@1472479372061/Measured-crack-width-allowing-water-infiltration.png)
- <https://www.amazon.ca/MYNT-Stereo-Camera-Depth-Sensor/dp/B07DD4QZXH>

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- <https://www.ontario.ca/laws/regulation/020239>
- <https://www150.statcan.gc.ca/n1/pub/16-002-x/2009001/tbl/transpo/tbl001-eng.htm>
- <http://www.mto.gov.on.ca/english/highway-bridges/ontario-bridges.shtml#:~:text=The%20Ministry%20of%20Transportation%20owns,professional%20engineer%20supervises%20all%20inspections.>

## Paper citations:

- Hoskere, Vedhus, et al. "MaDnet: multi-task semantic segmentation of multiple types of structural materials and damage in images of civil infrastructure."
- An, Yun-Kyu, et al. "Deep learning-based concrete crack detection using hybrid images." *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2018*. Vol. 10598. International Society for Optics and Photonics, 2018.