Deep Residual Net with Transfer Learning for Image-based Structural Damage Recognition

Yuqing Gao[1], Kevin Li[2], Khalid M. Mosalam[1] and Selim Günay[1]

1. Department of Civil and Environmental Engineering, UCB; 2. Department of Industrial Engineering & Operations Research, UCB

Abstract

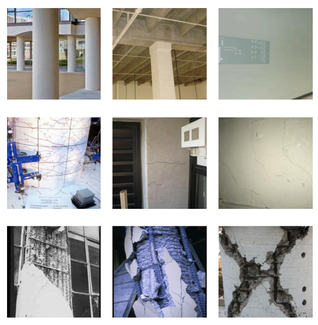
This poster aims to implement the state-of-art Deep Residual Net (ResNet) into traditional Civil Engineering areas, the study of images of structural damage recognition. With a labeled tiny dataset provided by Structural ImageNet, instead of training whole Convolutional Neural Network (CNN), Transfer Learning with fine-tuning were applied to ResNet-50 and ResNet-101 Models. Promising results were achieved, and Local Interpretable Model-agnostic Explanations (LIME) was applied to offer insights on the CNN via visualization.

Introduction

In this data explosion epoch, vision-based structural health monitoring and rapid damage assessment after natural hazards have become new focuses in civil engineering, and structural images, as the media, play a more important role in these fields studies. With the support of PEER database and NEEShub, a Structural ImageNet is established with labeled images. Meanwhile, AI and Machine Learning technologies are developing rapidly, especially in Deep Learning. Boosting with development of GPU and ImageNet challenge, Deep Learning in computer vision made a giant progress. Thus, it is a good chance to implement the state-of-art Deep Learning technologies to civil engineering areas such as image of structural damage recognition.

Beam Column / Wall

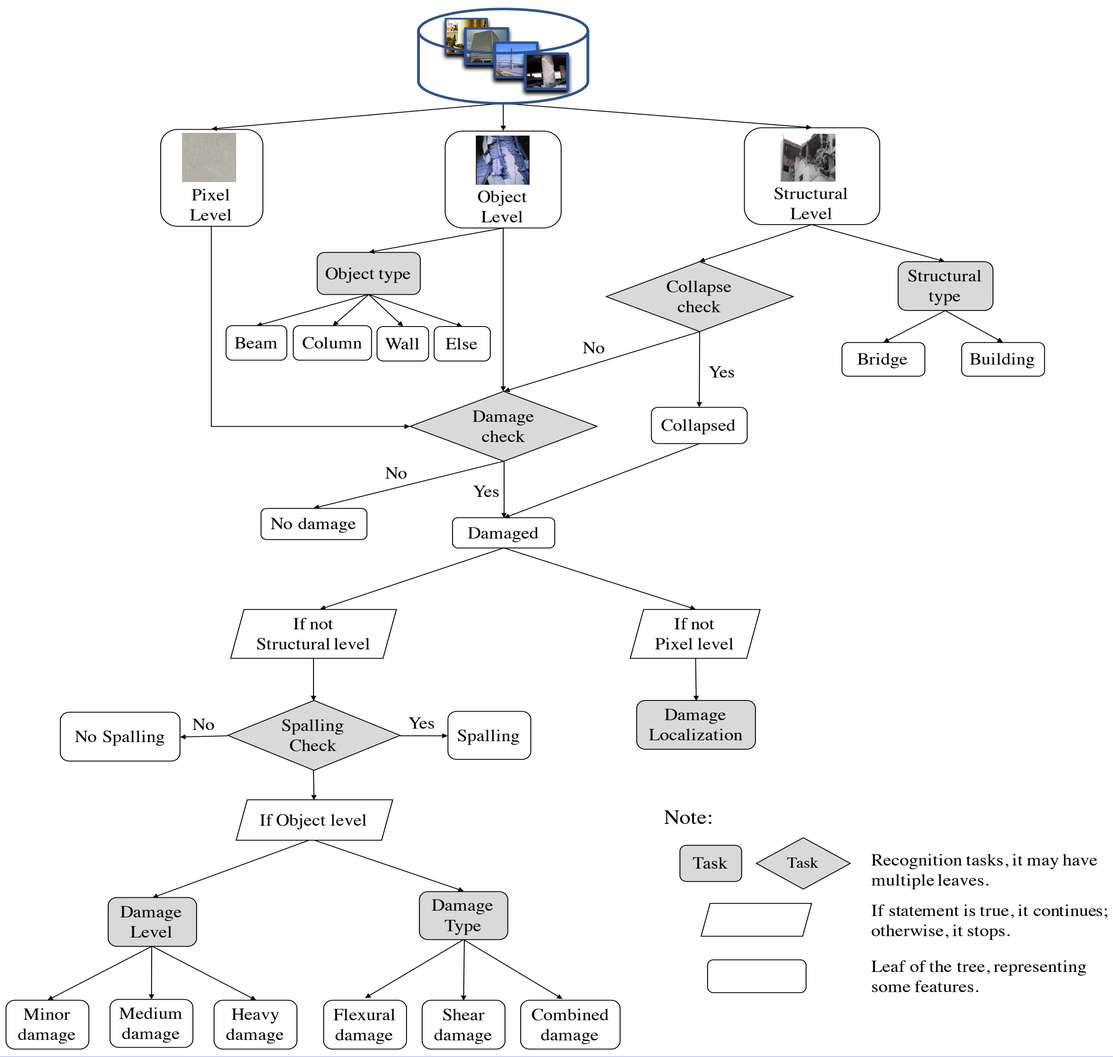
No spalling / Spalling



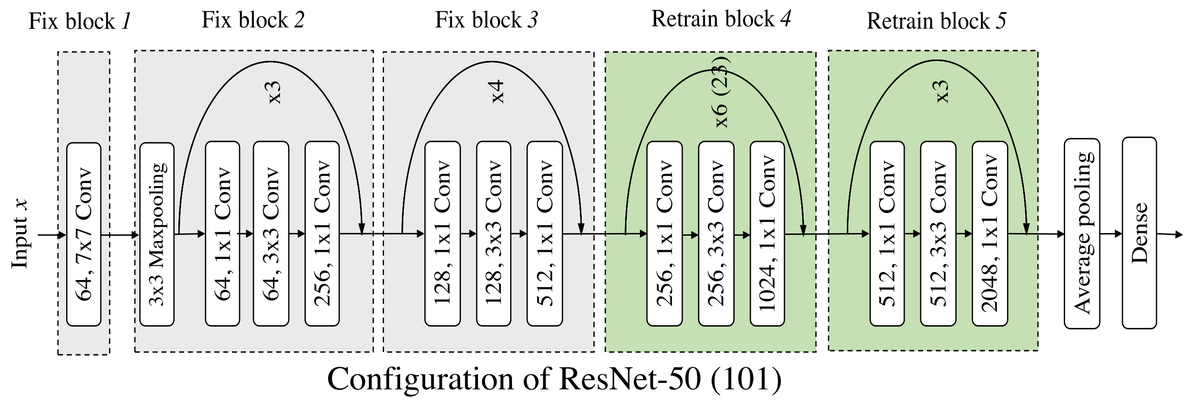
No damage/ Minor damage/ Heavy damage

No damage/ Flexural damage/ Shear damage/ Combined damage

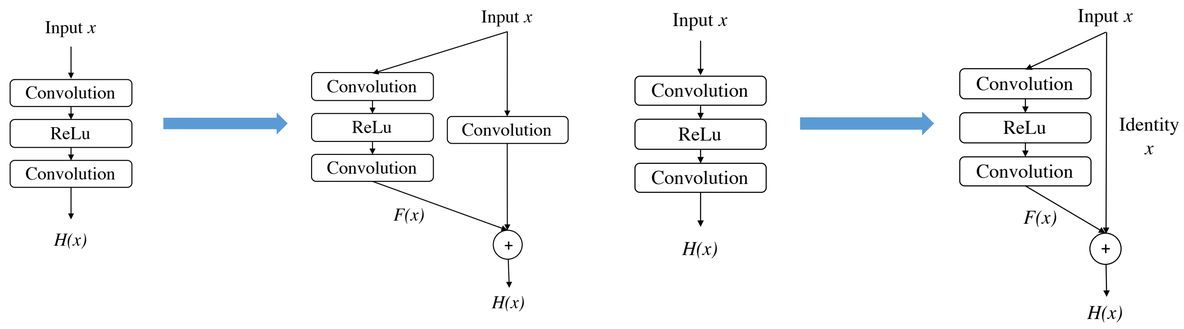
Structural ImageNet



Deep Residual Network with Transfer Learning



Configuration of ResNet-50 (101)

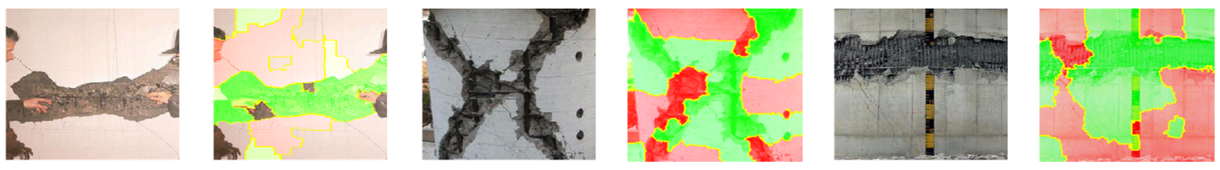


Convolutional shortcut

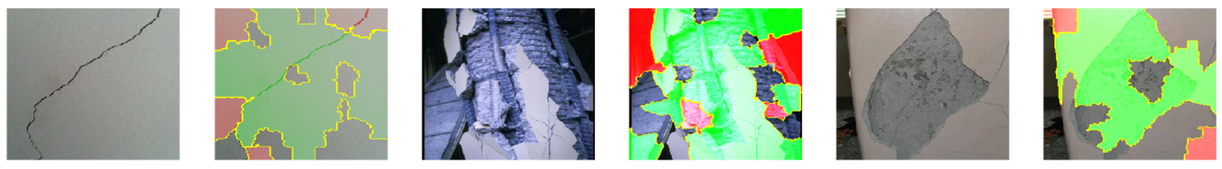
Identify mapping

Results & Visualization

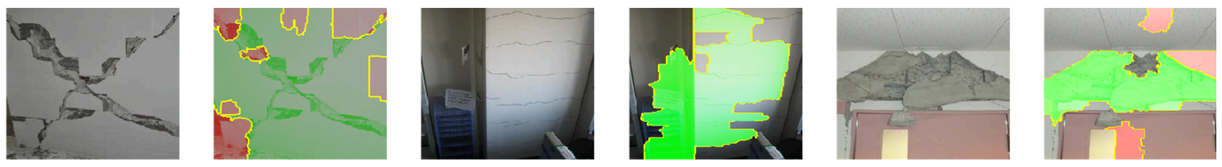
(a) Component type identification



(b) Spalling condition check



(c) Damage level evaluation



(d) Damage type determination

Tasks		ResNet 50	ResNet 101
Component type	Binary	96.5% (93.5%)	98.0% (94.0%)
Spalling condition	Binary	99.2% (88.5%)	98.5% (92.0%)
Damage level	3-classes	92.2% (90.5%)	97.0% (91.5%)
Damage type	4-classes	90.0% (72.0%)	94.5% (74.5%)

Acknowledgement

The author would like to acknowledge the funding support of TBSI, and appreciate the assistance from Graduate student Luka Liang, Yujia Xu and Renjie Wu.