StruX: Structural Damage Classification for Post-Disaster Recovery

CS 229 Final Project Spring 2019

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Motivation

Structural health monitoring (SHM) and rapid damage assessment after natural hazards and disasters have become an important focus in civil engineering. Nowadays, structural damage recognition using images is one of the important topics in SHM and forensics engineering, which greatly relies on human visual inspection and experience. It is time to implement the state-of-art DL technologies in civil engineering applications and evaluate its potential benefits.

Problem Statement

The objective of project is to classify the damage type (i.e. no/flexural/shear/combined damage) and the damage level (i.e. no/minor/moderate/heavy damage) of the structures, which is mainly assessed by human experience traditionally. The classes of images change based on different datasets including binary classification and softmax classification.

Raw input data in our models is RGB image from PEERHub ImageNet challenge[1]. The shape of image is 224×224×3. Before training in the model, the feature are normalized to accelerate modal training. Also batch normalization is used in the baseline model and improved model.

Damage Type

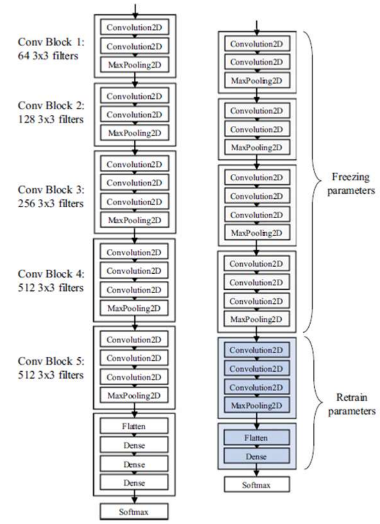
Spalling Condition

Collapse Mode

Damage State

Models & Improvement

Three baseline models are used in preliminary test including AlexNet, VGG16 and ResNet. Fine-tuning are not used in baseline models to investigate the performance of naive models without any pre-trained parameters. And the fine-tuning are used to improve the model. Firstly the pre-trained modal parameters are obtained from ImageNet. Based on the number of modal layer, parameters in lower-level layers are frozen to accelerate the training and extract the feature of images (pixel gradients, texture and color). Parameters in higher-level conv-blocks and fully-connected layers are unfrozen and kept updated in the training.



VGG16 Structure **VGG16 with Fine-tuning**

Hyperparameter Tuning

The hyperparameter are tuned for improving the performance of models.

※ Dropout Rate

※ L1/L2 Regularization

※ Learning rate & Learning rate decay

※ # of Conv blocks frozen & unfrozen

※ SGD & RMSProp & Adam & Momentum

Additional models are trained to find the optimal model to predict the structural damage including MobileNet, MobileNetV2, VGG19 and InceptionV3.

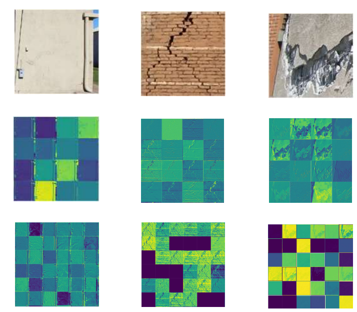
	Task	Spalling Condition	Collapse Mode	Damage Type
Baseline Model	AlexNet	59.61%	53.30%	56.20%
	VGG16	65.63%	58.10%	57.70%
	ResNet50	57.94%	51.20%	52.10%
Improved Model	VGG16	84.76%	67.40%	64.11%
	VGG19	84.34%	66.50%	62.34%
	ResNet50	79.02%	62.30%	58.42%
	MobileNet	84.75%	68.20%	61.90%
	MobileNetV2	85.45%	69.11%	64.50%
	InceptionV3	80.50%	63.20%	57.14%
Paper		91.50%	—	68.80%

Prediction Accuracy Summary

Input Layer

Conv Block1

Conv Block3

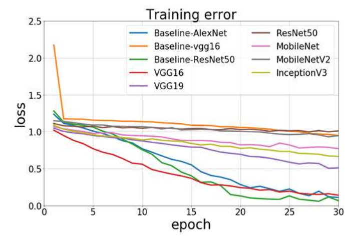


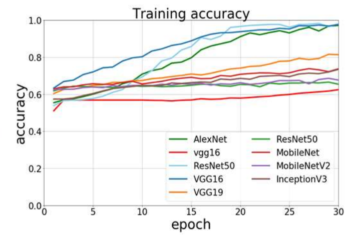
Softmax Output

$$\begin{Bmatrix} 9.12\times10^{-1} \\ 5\times10^{-2} \\ 3\times10^{-2} \\ 8\times10^{-3} \end{Bmatrix} \quad \begin{Bmatrix} 9.8\times10^{-2} \\ 6.32\times10^{-1} \\ 2.47\times10^{-1} \\ 2.3\times10^{-2} \end{Bmatrix} \quad \begin{Bmatrix} 2\times10^{-3} \\ 5\times10^{-2} \\ 8.21\times10^{-1} \\ 1.27\times10^{-1} \end{Bmatrix}$$

Label 0 (No Damage) 1 (Minor Damage) 2 (Heavy Damage)

Result Analysis





The learning curves including training error and accuracy are shown in the figure. Models without fine-tuning have large variance and issue of over-fitting, which can be found from the huge difference between training accuracy and test accuracy. The issue of overfitting is controlled after applying fine-tuning, dropout and L2 regularization. But bias issue occurs after fine-tuning, where accuracy of training set decrease dramatically.

From table, MobileNetV2 has highest accuracy among those models, which is close to the result from paper[1].

Conclusion & Future Work

Deep convolutional Neural Network is implemented to classify structural damage. VGG16 and MobileNetV2 perform fast computation but has limited accuracies for multi-classes. The performance can be improved through fine-tuning and hyperparameter tuning.

Besides the three tasks, further recognition such as damage localization and quantification can be studied, which can also be combined with drone or satellite imagery in post-disaster structural recognition.

The prediction accuracy is not as high as expected. The reason is probably from the bad input image. Image segmentation is probably adopted in pre-processing

Reference

[1] Gao, Y. and Mosalam, K. M. (2018), Deep Transfer Learning for Image-Based Structural Damage Recognition. Computer-Aided Civil and Infrastructure Engineering.