Meta-learning Convolutional Neural Architectures for Multi-target Concrete Defect Classification with the COncrete DEfect BRidge IMage Dataset

CVPR LONG BEACH CALIFORNIA June 16-20, 2019

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Overview

- Multi-class multi-target image dataset with defects in context of concrete bridges.
- Evaluation and comparison of best-practice CNN architectures for our task.
- We adapt and contrast two architecture search methods, MetaQNN and ENAS.

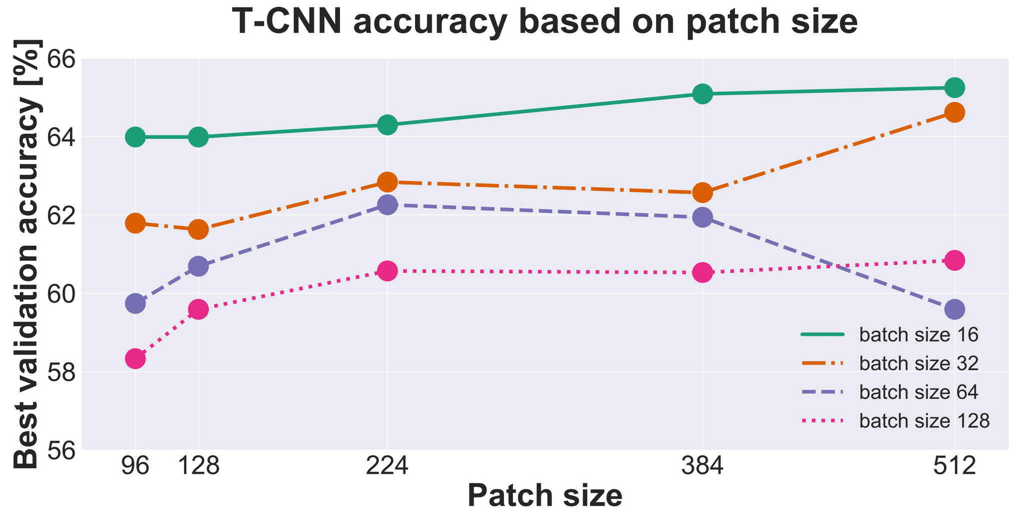
CODEBRIM dataset

1590 high-resolution images, 30 unique bridges, at different scales and resolutions. Overlapping defect classes: crack, efflorescence, spalling, exposed bars, corrosion.

Pixel-wise labels expensive → 5354 annotated bounding boxes to learn from context.

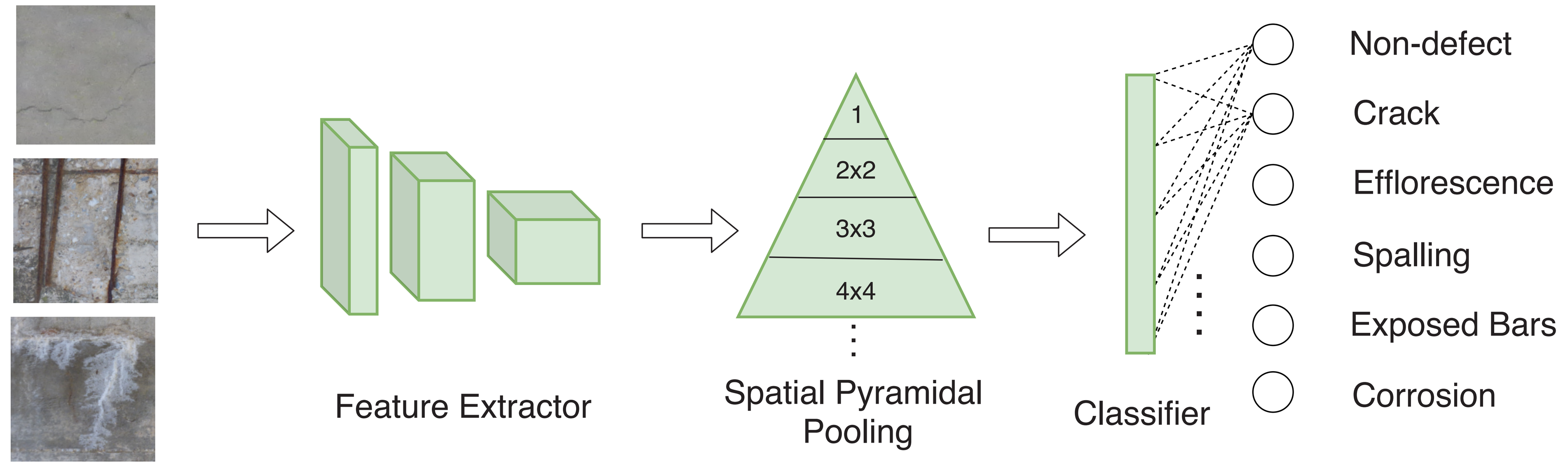
Hyper-parameters

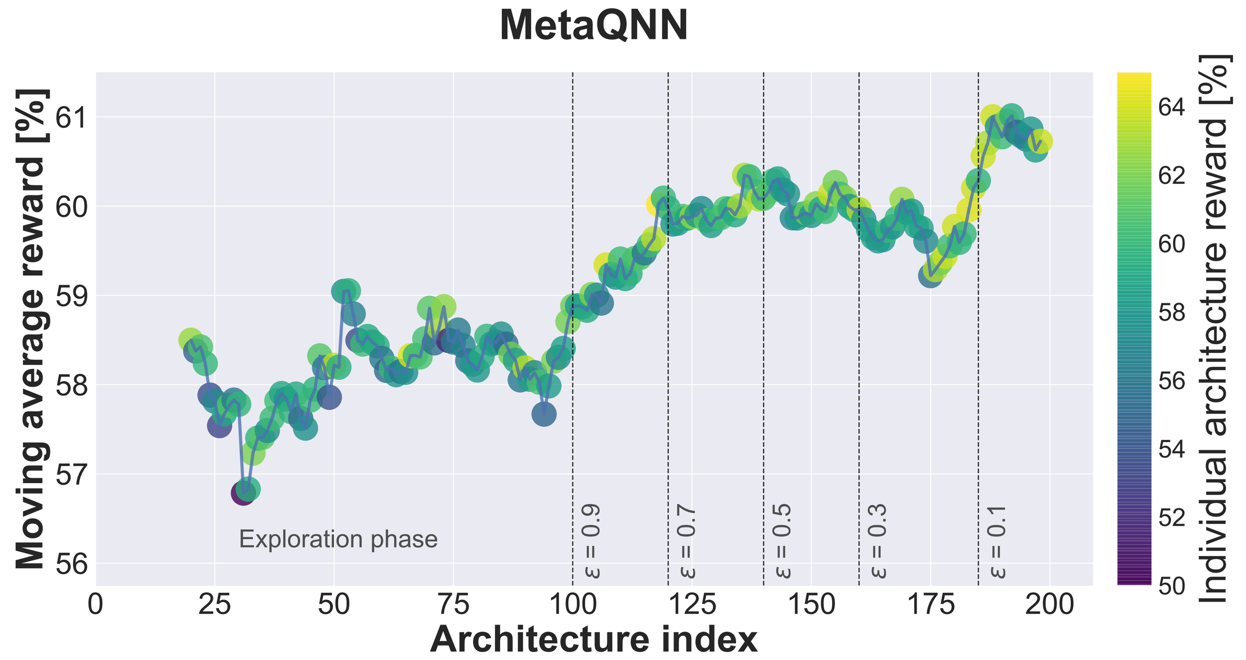
Validation set based search for cyclical learning rates, batch and patch sizes.

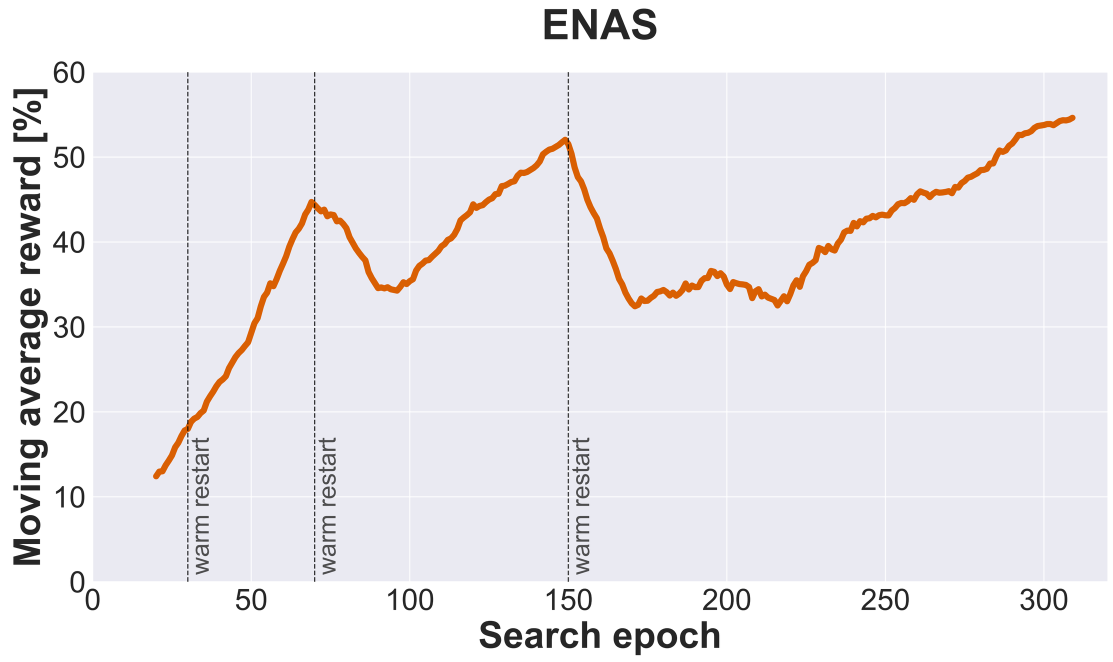


Learning concrete defects from context with meta-learned neural architectures

- We adapt and compare MetaQNN (Q-learning) and ENAS (policy gradients with RNN) for our multi-target classification task.
- Search space includes: convolutional, pooling and fully-connected layers with kernel sizes, number of units, strides and skip-connections. We also use batch-normalization and cyclical learning rates to provide a fair comparison.
- We further search for spatial pyramidal pooling to allow for flexible input image size and ratio and incorporate scale invariance.







Architecture	Multi-target accuracy [%]		Params [M]	Layers
	best val	bv-test		
Alexnet	63.05	66.98	57.02	8
T-CNN	64.30	67.93	58.60	8
VGG-A	64.93	70.45	128.79	11
VGG-D	64.00	70.61	134.28	16
WRN-28-4	52.51	57.19	5.84	28
Densenet-121	65.56	70.77	11.50	121
ENAS-1	65.47	70.78	3.41	8
ENAS-2	64.53	68.91	2.71	8
ENAS-3	64.38	68.75	1.70	8
MetaQNN-1	66.02	68.56	4.53	6
MetaQNN-2	65.20	67.45	1.22	8
MetaQNN-3	64.93	72.19	2.88	7

Transfer learning

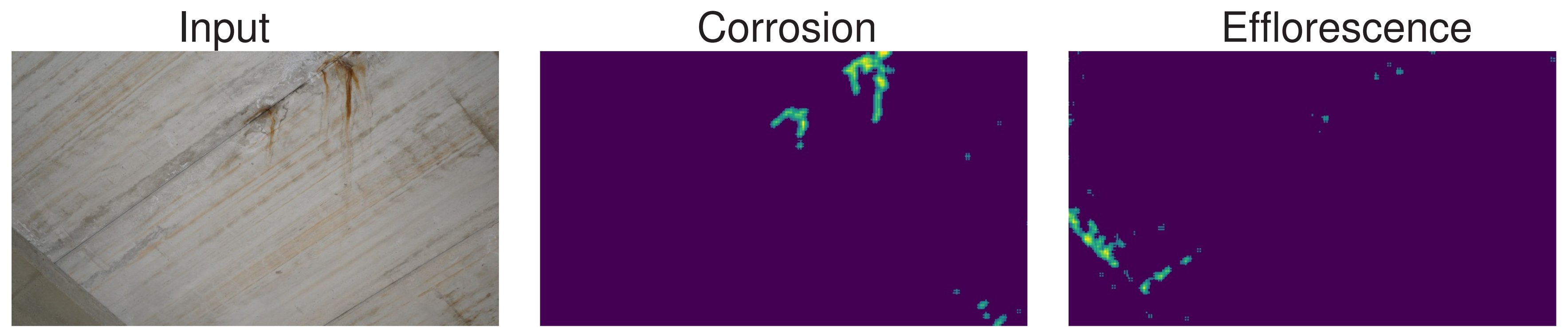
Architecture	Source	Accuracy [%]	
		best val	bv-test
Alexnet	ImageNet	60.53	62.87
VGG-A	ImageNet	60.22	66.35
VGG-D	ImageNet	56.13	65.56
Densenet-121	ImageNet	54.71	57.66
Alexnet	MINC	60.06	66.50
VGG-D	MINC	61.47	67.14

Conclusion - takeaways

- High-resolution multi-target image dataset in a real-world application domain.
- Meta-learning essential to find suitable architectures for the domain. Outperforms literature baselines in terms of higher accuracy, fewer layers and parameters for multi-target concrete defect classification.
- A fair comparison with similar search spaces and hyper-parameters shows that MetaQNN and ENAS perform equally well in our multi-target domain.
- Architecture improvements as seen on ImageNet do not show similar improvements on our task, highlighting the need for different domain datasets.

Outlook: detection and semantic segmentation

Architecture has been trained for defect classification in context → slide the model over high-resolution images to obtain multi-target semantic segmentation:



Project open-source content

Dataset: `https://zenodo.org/record/2620293`
Code: `https://github.com/ccc-frankfurt/meta-learning-CODEBRIM`

Acknowledgments

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 687384 .