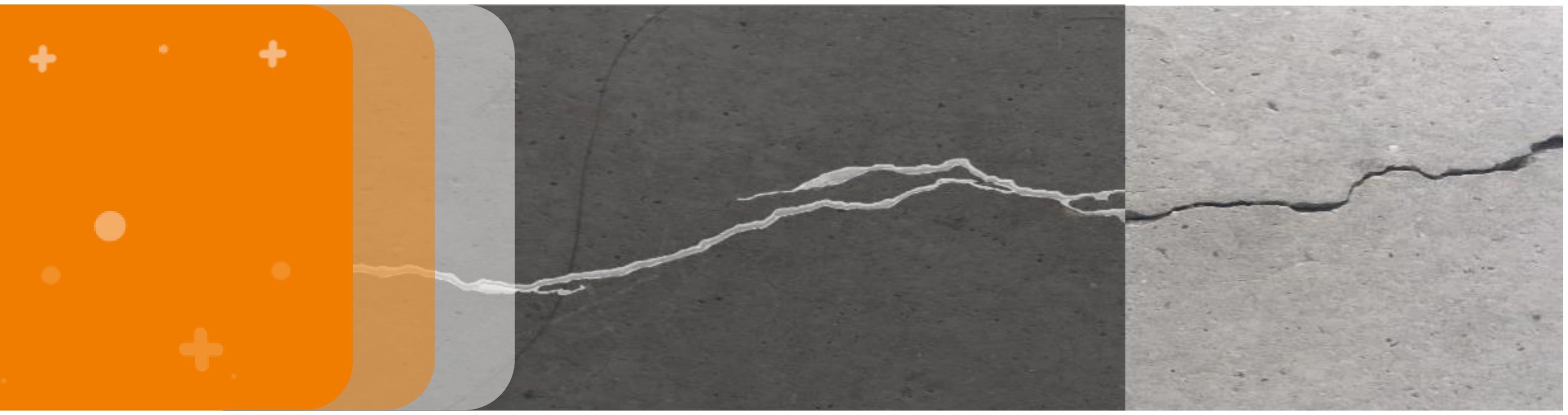


Image-based Segmentation of Concrete Cracks

Project Goal

Infrastructure needs to be monitored reliably for wear and tear. Manual inspections are costly and not always consistent in quality. If changes over time are to be detected, inspections need to be regular and comparable.

Professionals in structural health monitoring can benefit greatly from automated solutions. This use case demonstrates a deep learning based tool that can automatically detect concrete cracks on pixel level. With the help of such pixel-wise classification (segmentation) cracks can analyzed regarding width and heights and compared over time.

Dataset Used

We made use of a dataset of 458 high-resolution RGB pictures showing different concrete cracks. For each image, a binary mask indicating the position of the crack was hand-drawn as a label.

The larger images were then mosaicked into smaller tiles of 256 x 256 pixels. This ensured a consistent input size for the neural network and a manageable memory load. Tiles that did not contain any cracks where removed to reduce the already large imbalance in the ratio of cracked/not-cracked pixels. In total this resulted in a dataset of 12,310 labeled tiles.

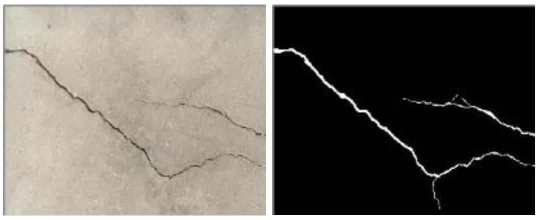


Image and corresponding label mask
(3024 x 4032)

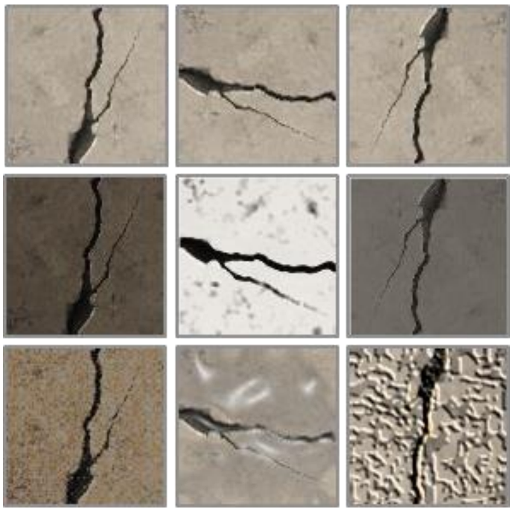
Input tiles (256 x 256)

Challenges

Training a neural network requires a large amount of training data. Generating the pixel mask labels is a time consuming tasks. Label quality is crucial to ensure model performance.

For different applications the structures that need to be analyzed can differ greatly. A model trained solely on cracks in smooth concrete surfaces will not generalize well to for example asphalt or brick walls. The same applies to the lighting conditions and resolutions of the input data. To overcome this challenge we applied extensive data augmentation.

Examples of structural variety for
different applications



Augmentation Examples

Data Augmentation

Our dataset already contained a range of different surfaces. To further increase the performance of our model we made use of different augmentation techniques that can simulate various lighting conditions and structural variances.

Augmentation techniques that we used randomly performed rotations and mirroring, changed hue, saturation and brightness as well as added noise and patterns to the input images

Data augmentation has the benefit of reducing the risk of overfitting and can make model performance more robust. This also ensures that our approach can be transferred to similar cases with minimal re-training.

97%

Of all cracked pixels were accurately detected

Applied Methods

We applied the Deep Lab v3 neural network architecture, the current state-of-the-art in image segmentation. The model and training pipeline were implemented with PyTorch.

Model performance was evaluated based on the dice coefficient as well as true positive rate (TPR). The former indicates how well the predicted crack pixels align with the ground truth. TPR measures how many crack pixels were accurately detected by the model.

The final model achieved a dice coefficient of 88% and a TPR of 97% on the validation set. This performance is suitable for automated crack detection applications.

Predictions where then denoised using morphological opening. Stitching the tiles back together we could analyze the entire pictures regarding number of cracks as well as crack length and width.

Input, Ground Truth, and Prediction

Project Outcome

The tool is capable of accurately detecting surface cracks on pixel level. Crack width and length can thus be automatically monitored.

For applications where images are consistently taken from the same locations, this allows analyzing changes in cracks and early detection of new cracks.

Potential Applications

Our tool is valuable for professionals in a range of fields working with structural health monitoring and infrastructure maintenance.

Given new labeled data of a transfer case, the model can be retrained and applied to detect cracks in a range of surfaces such as asphalt and other concrete structures.

In combination with geolocated UAV imagery it is possible to create a fully automated monitoring pipeline using this approach.