

| Title | Dataset Name | Dataset URL | Image | Classes | Split | Method Name | Accuracy of the model | Research Question | Pros and Cons | Citation |
|---|----------------------------|---|--------------------------------------|-----------------------|---|--|---|--|---|----------|
| Automatic Pixel-Level Pavement Crack Detection Using Information of Multi-Scale Neighborhoods | Crack Forest Dataset (CFD) | https://github.com/cuili-meng/CrackForest-dataset | 118 images | 2 — Crack / Non-Crack | 60% Train / 40% Test | PGM + SVM | F1 = 88%, Precision = 91%, Recall = 86% | How to detect cracks at pixel level using multi-scale info? | .Accurate, lightweight . Small dataset, lightweight sensitive | 1 |
| Automated Pavement Crack Segmentation Using U-Net-Based Convolutional Neural Network | Crack500 Dataset | https://github.com/yhleo/Crack500 | 6040 images (3792 train / 2248 test) | 2 — Crack / Non-Crack | U-Net (ResNet-34 encoder + SCSE + One-cycle LR) | U-Net (ResNet-34 encoder + SCSE + One-cycle LR) | F1 = 95.55%, Precision = 96.6%, Recall = 94.5% | How can U-Net + transfer learning improve pixel-level crack segmentation accuracy? | .High F1 accuracy .Uses transfer learning & SCSE .Limited dataset size .Sensitive to lighting/noise | 2 |
| Asphalt Pavement Crack Detection Based on CNN and Infrared Thermography | IR-Crack | https://github.com/lfangyu09/IR-Crack-detection | 448 images | 2 (crack/non-crack) | train:85.27% ,test:14.73% | CNN segmentation models: FPN, DeepLabv3, UNet-VGG19, UNet-ResNet101, | FPN: ~97% (visible & fusion), DeepLabv3: ~96% (fusion), Infrared images | Can CNN combined with IRT improve accuracy and efficiency of pavement | Fusion images with FPN give accurate, efficient crack detection, while infrared | 3 |

| | | | | | | | | | | |
|---|--|---|------------|-------------------|---|-------------------------------------|-----------------------------------|---|--|---|
| | | | | | | UNet, PSPNet, FCN | : 85–90% | crack detection under various conditions? | d-only images are less accurate and some models are resource-heavy. | |
| A potential crack region method to detect crack using image processing of multiple thresholding | German Asphalt Pavement Distress (Gap) | https://link.springer.com/article/10.1007/s11760-021-02055-8 | 509 images | Crack / Non-crack | Test set from 6 non-overlapping crops per image | MTM (Multiple Thresholding Method). | Precision 82%, Recall 81%, F1 83% | | Pros: Adaptive, noise reduction Cons: Thicker cracks may be missed, sensitive to lighting | 4 |
| | | | | | | | | | | |

1. D. Ai, G. Jiang, L. Siew Kei and C. Li, "Automatic Pixel-Level Pavement Crack Detection Using Information of Multi-Scale Neighborhoods," in IEEE Access, vol. 6, pp. 24452-24463, 2018, doi: 10.1109/ACCESS.2018.2829347.

keywords: {Roads;Probability;Support vector machines;Signal processing algorithms;Robustness;Topology;Surface cracks;Pavement crack detection;probability map;multi-scale neighborhoods;probabilistic generative model;support vector machine},

2. S. L. H. Lau, E. K. P. Chong, X. Yang and X. Wang, "Automated Pavement Crack Segmentation Using U-Net-Based Convolutional Neural Network," in IEEE Access, vol. 8, pp. 114892-114899, 2020, doi: 10.1109/ACCESS.2020.3003638.

keywords: {Convolutional neural networks;Image segmentation;Network architecture;Training;Deep learning;Feature extraction;Convolutional neural network;deep learning;fully convolutional network;pavement crack segmentation;U-Net},

3. F. Liu, J. Liu and L. Wang, "Asphalt Pavement Crack Detection Based on Convolutional Neural Network and Infrared Thermography," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 11, pp. 22145-22155, Nov. 2022, doi: 10.1109/TITS.2022.3142393.

keywords: {Computational modeling;Image segmentation;Complexity theory;Cameras;Measurement;Convolutional neural networks;Asphalt;Crack detection;convolutional neural network;infrared thermography;asphalt pavement},

4. Chen, C., Seo, H., Jun, C. et al. A potential crack region method to detect crack using image processing of multiple thresholding. SIViP 16, 1673–1681 (2022).
<https://doi.org/10.1007/s11760-021-02123-w>