

Title	Dataet Name	Dataset URL	Image	Class- es	Split	Met- hod Name	Acc-ur acy of the model	Rese- arch Ques- tion	Pros and Cons	Citati -on
Automatic Pixel Level Pavement Crack Detection Using Information of Multi Scale Neighborhoods	Crack Forest Dataset (CFD)	<a href="https://github.com/cuili-meng/CrackForest-dataset">https://github.com/cuili-meng/CrackForest-dataset</a>	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 MultiScale info?	.Accurate, lightweight . Small dataset, .lighting sensitive	1
Automated Pavement Crack Segmentation Using U-Net Based Convolutional Neural Network	Crack 500 Dataset	<a href="https://github.com/yhlleo/Crack500">https://github.com/yhlleo/Crack500</a>	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 UNet + transfer learning improve pixel level Crack segmenta-tion 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	<a href="https://github.com/lfangyu09/IR-Crack-detection">https://github.com/lfangyu09/IR-Crack-detection</a>	448 images	2 (crack/ Non crack)	Train: 85.25 %,test: 14.73 %	CNN segmen-tation models: FPN, DeepL-abv3, UNet VGG19, UNet ResNeT101, UNet, PSPNet, FCN	FPN: ~97% (visible & fusion), DeepL Abv3: ~96% (fusion), Infrared images: 85–90%	Can CNN combined with IRT improve accuracy and efficiency of Pavement crack DetectiOn Under various Condi-tions?	Fusion Images with FPN give accurate, efficient Crack detection, While infrared Only images are less accurate and some Models Are resource heavy.	3

A potential crack region method to detect crack using image processing of multiple thresholding	German Asphalt Pavement Distress (Gap)	<a href="https://link.springer.com/article/10.1007/s11760-021-02055-8">https://link.springer.com/article/10.1007/s11760-021-02055-8</a>	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
---	--	---	------------	-------------------	---	-------------------------------------	-----------------------------------	--	--	---

### Citations:

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.
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.
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.
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>