

Deep Learning for Pavement Distress Detection

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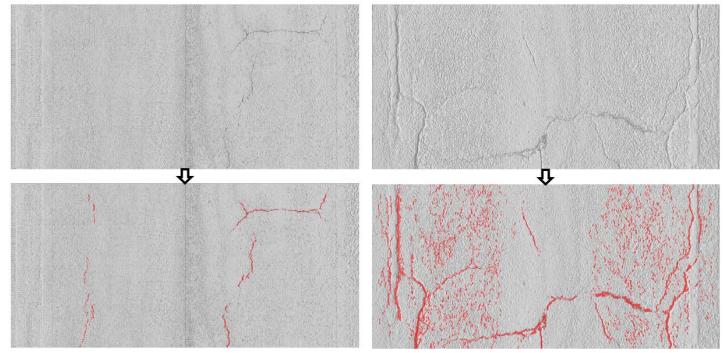
Challenges of Cracking Automation

- Complexity
 - Pavement Surface: A Highly Complicated Environment with Extensive Uncertainties
 - Distress Identification: Challenging Even for Well-trained Human Operators

- Diverse Pavement Surface Texture
- Various Presences of Pavement Distresses

Common Failures

• Inconsistent Accuracies for Pavement with Various Texture



Smooth Pavement Surface

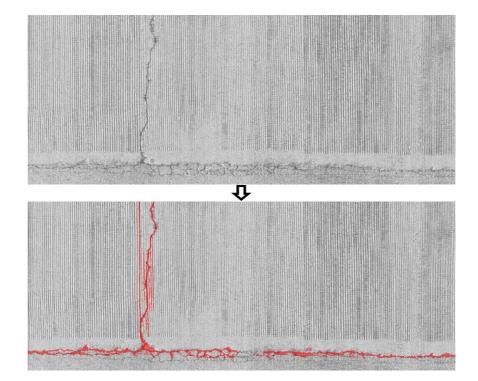
Highly Textured Pavement Surface

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Common Failures

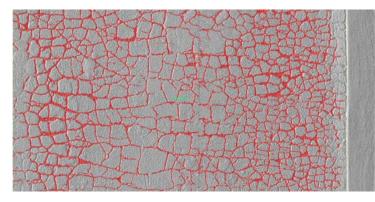
• Interference from Other Patterns

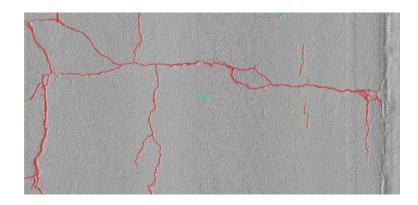


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Objectives

- Automated Crack Detection
 - Find the Actual Location of Distresses with Pixel-Perfect Accuracy
- Automated Crack Classification
 - Label Distress Types





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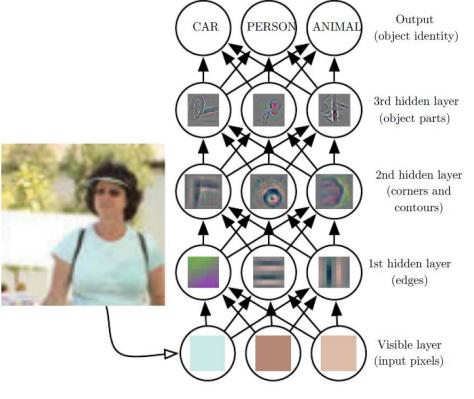
Deep Learning

- Strong Learning Ability
 - Learning from Experiences
 - Exploiting Understanding on New and Unlabeled Examples
- Versatility
 - A Deep Learning Network Can Detect Multiple Types of Pavement Distresses
- Enhanced Reliability
 - Feed with Exhaustive Variations of Pavement Distresses

Compositional Model for Image Recognition

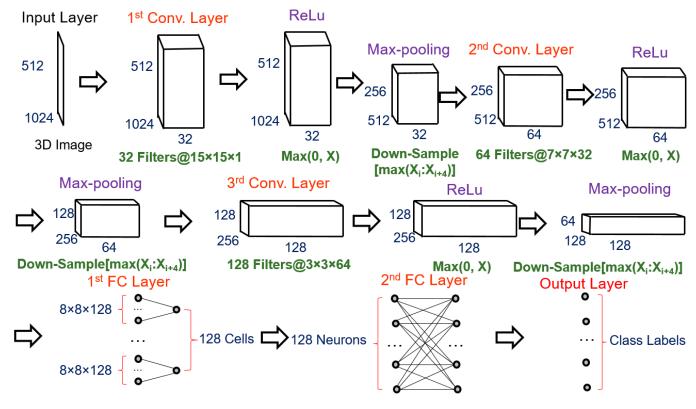
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(Goodfellow et al., Deep Learning, 2016)

Convolution Neural Network for Distresses

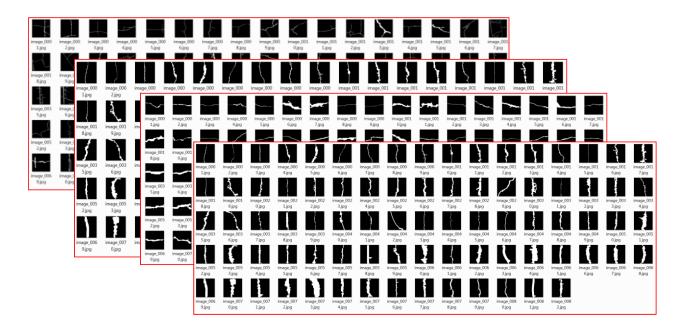


- 11 Layers
- 1,246,496 Parameters

Convolution Neural Network for Distresses

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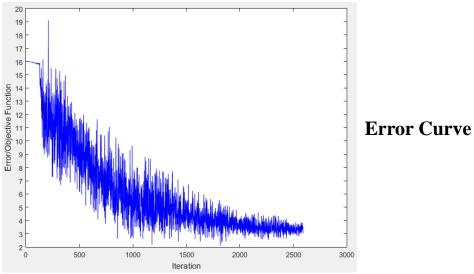
• Recognize Pavement Distresses in Small Cells



• Recognition Accuracy > 96%

# of Samples	# of Samples with False- positive Errors	# of Samples with False- negative Errors	False-positive Error	False-negative Error	Accuracy
23,296	163	684	0.7%	2.936%	96.364%

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• Learned Filters

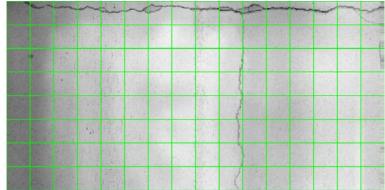
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1 st Convolution Layer							as.	2 nd Convolution Laver							•	3 rd Convolution Layer								

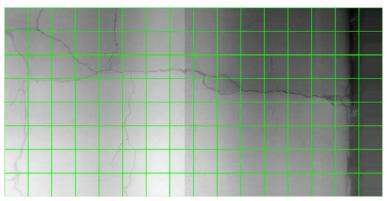
32@15×15×1

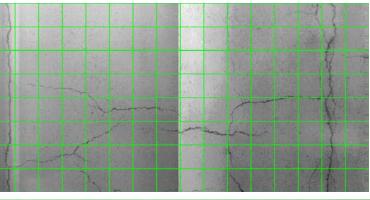
 2^{nd} Convolution Layer 64@7×7×32 3^{rd} Convolution Layer $128@3 \times 3 \times 64$

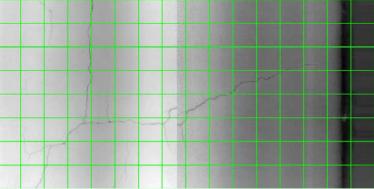
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• Example Images with No Recognition Errors

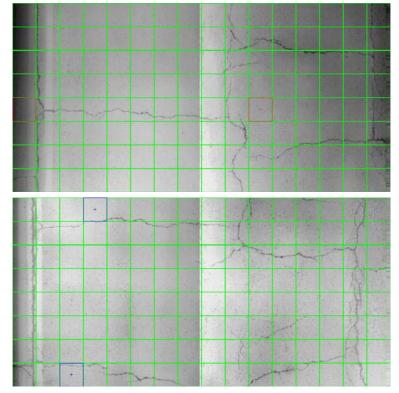


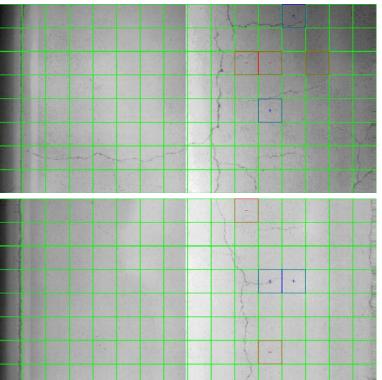






• Example Images with False-positive or False-negative Errors





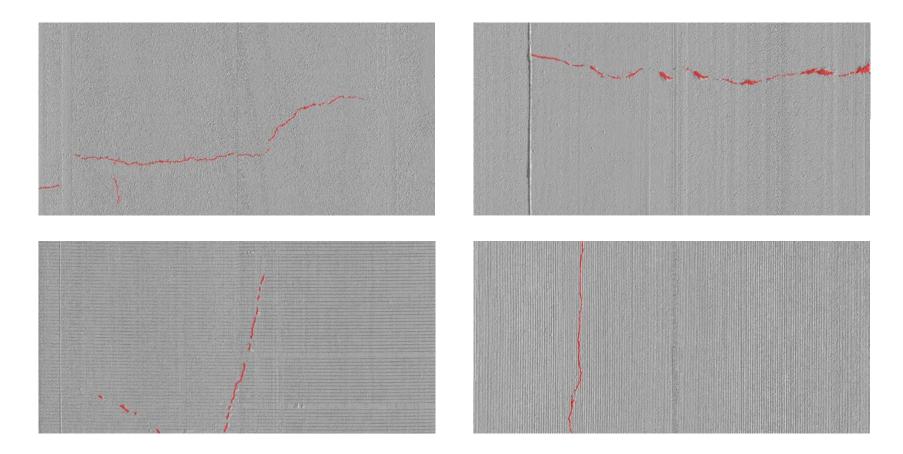


14

Image Library

- Data Type
 - 3D Data & 2D Images
- Image Library Size
 - 2016-2017: 150,000 3D Images + 150,000 2D Images
 - 2017-2020: 1,000,000 3D Images + 1,000,000 2D Images
- Ground Truth
 - Manually Marked
- Diversity
 - All Typical Variations of Pavement Distresses

Typical Samples in Image Library



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Future Tasks

- Exhaustive Image Library
 - 3D Pavement Data & 2D Pavement Image
 - All Variations of Pavement Distresses
 - Manually Marked Ground-truth
- Long-term Training & Optimization
 - Training on Entire Network Using Gradient-based Algorithm
 - Sufficient Computational Horsepower
- Self-taught Learning
 - Unsupervised Learning from Unlabeled Data;
 - Progressive Improvements in Real-time Applications
- Real-time Application
 - Parallel Computing to Reduce Processing Time