Deep Learning System for Automated

Cracking Survey & Its Performance with Pixel Accuracy: CrackNet

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Supported by FAA, FHWA, several DOTs, and Users Worldwide

2017-11-16, Denver Marriott West, Road Profiler Users Group (RPUG)

Challenges of Cracking Automation

Complexity

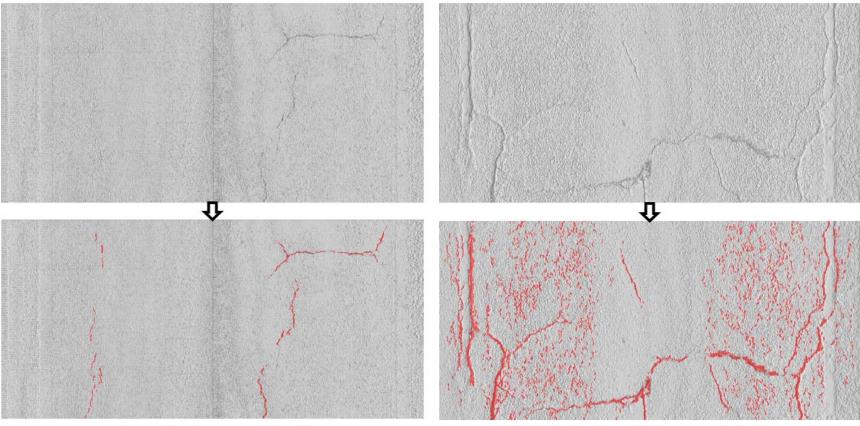
- Pavement Surface: A Highly Complicated Environment with Extensive Uncertainties & Variations on Surface Condition
- Distress Identification: Challenging Even for Well-Trained Human Operators
- > Diverse Pavement Surface Texture: Open-Graded
- > Presence of Non-Cracking Pavement Distresses

Limitations of Traditional Algorithms

- Simple Methodology & Specific Assumptions
- Not Fully Validated on Diverse Pavement Surfaces
- Limited or No Learning Capabilities
- Inconsistent Precision & Bias Levels on Different Roads

Common Failures

- Inconsistent Accuracies for Pavement with Various Texture
- Requirement of Substantial Human Intervention and Manual Processing

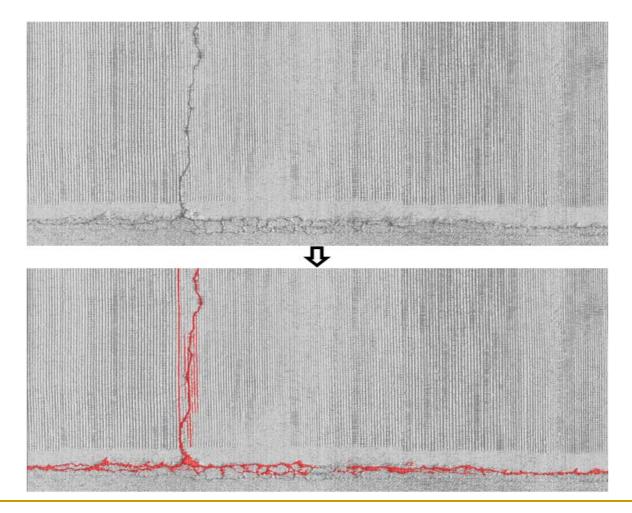


Smooth Pavement Surface

Highly Textured Pavement Surface

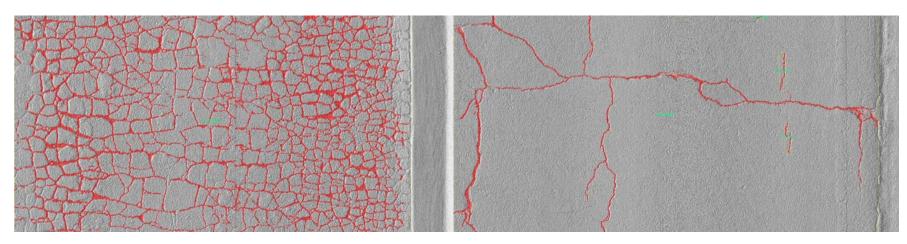
Common Failures

□ Interference from Other Patterns

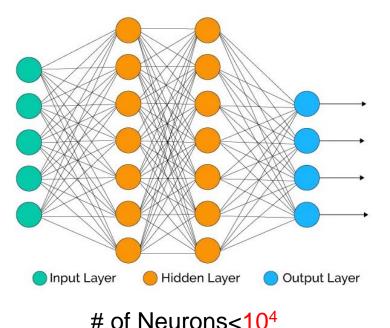


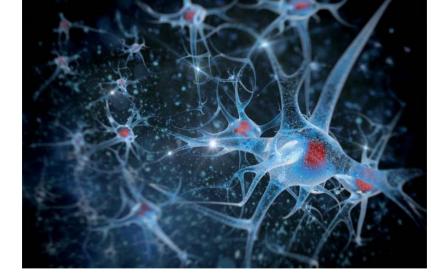
Ultimate Objectives for True Automation

- Cracking with Pixel-Perfect Accuracy for Any Pavements
- Crack Classification: Label Distress Types
- No Human Intervention in Production with Acceptable and Consistent Precision & Bias Levels for Any Pavements
- **Real-Time Processing in a Single Workstation**
- Meeting New Protocol Requirements



Traditional Artificial Neuron Network (ANN)





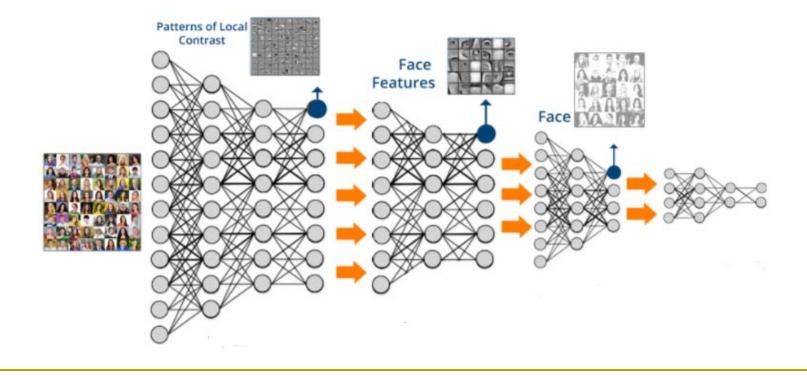
of Neurons=10¹¹ (Human Brain)

Shallow Abstraction

- > Limited Number of Layers & Neurons
- Cannot Fully Reflect the Complexity of Problems
- Limited Amount of Data

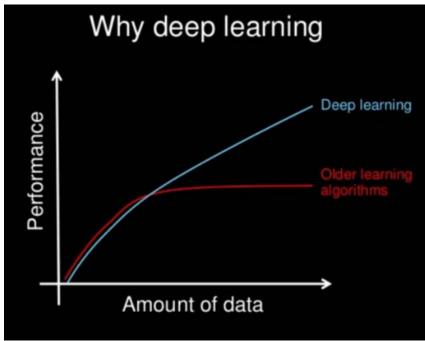
Deep Learning: New Generation of ANN

- □ Deep Abstraction: # of Layers: 10¹-10³, for Complex Problems
- □ Complex Connections Among Neurons: 10²-10⁴ per Neuron
- **Content** Enhanced Reliability: Exhaustive Variations of Example Data
- High-Performance Processing: Critical

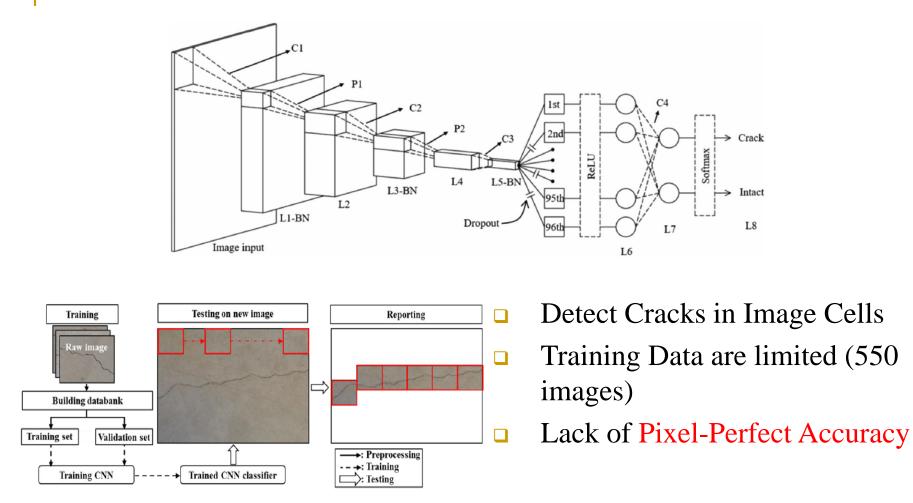


Why Deep Learning?

- Strong Learning Ability and Versatility
 - > A DL Network: Multiple Types of Objects (Pavement Distresses)
- Enhanced Reliability
 - Feed with Exhaustive Variations of Examples
- Learning/Knowledge Accumulation
 - Similar to Human Learning Process



CNNs for Cracking Detection (Cell Image)



Deep Learning-Based Cracking Damage Detection Using CNNs, Computer-Aided Civil and Infrastructure Engineering, 2017

DL System Design for Cracking (Pixel Based)

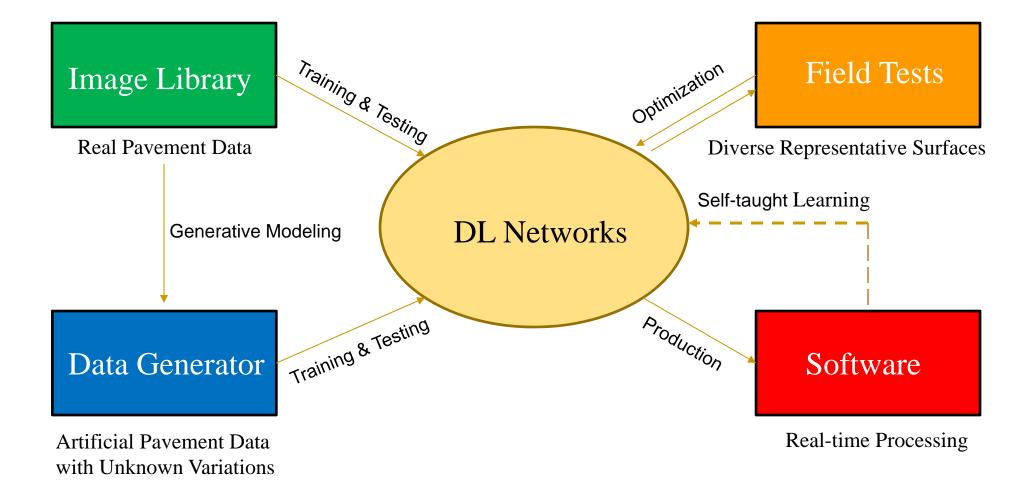
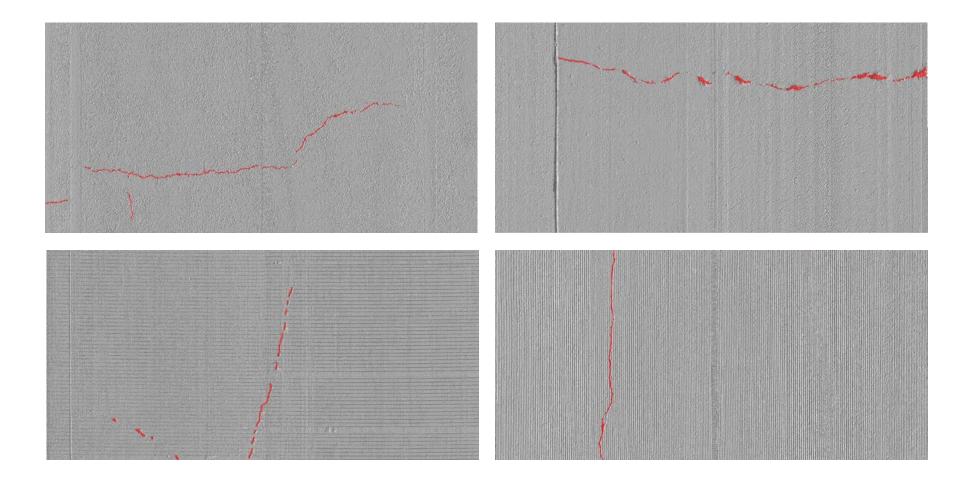


Image Library

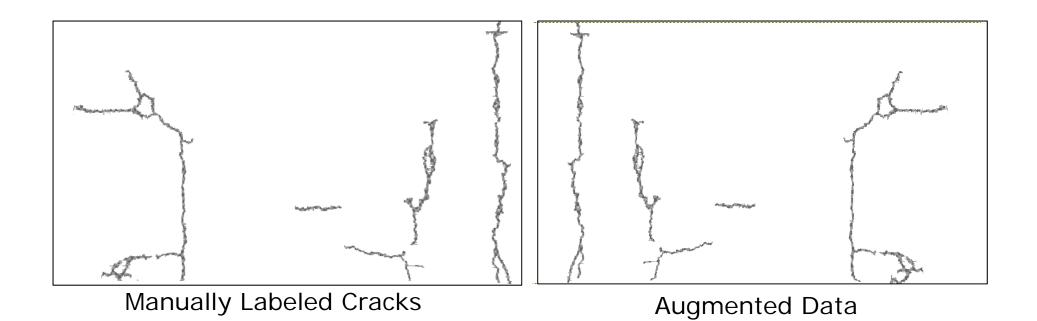
- Source Data Type
 - > 3D Data & 2D Images
- Image Library Size
 - > 2016-2017: 10,000 3D Images + 10,000 2D Images
 - > 2017-2020: 50,000 3D Images + 50,000 2D Images
- Ground Truth with Pixel-Perfect Accuracy
 - Manually Marked, Verified; Automated/Augmentation
- Diversity
 - > All Typical Variations of Pavement Distresses

Typical Labeled Examples of Image Library

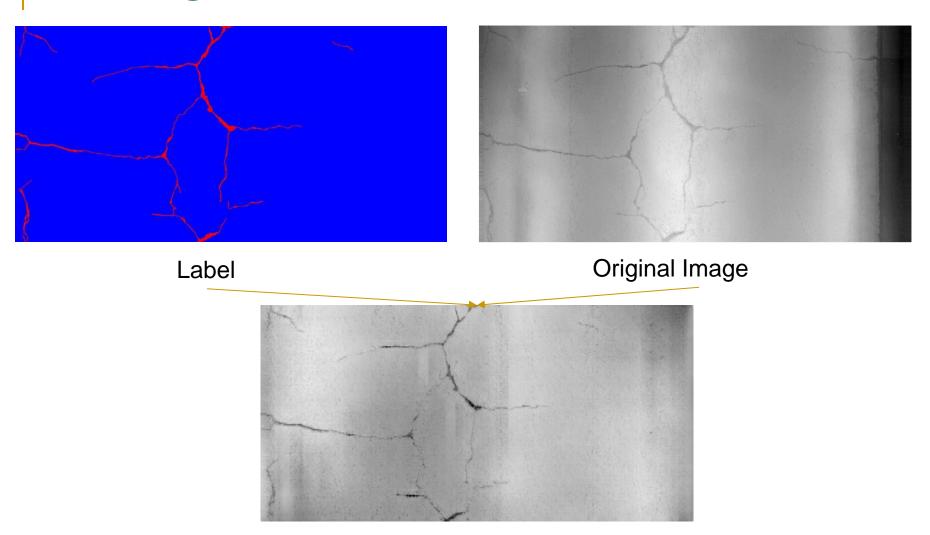


Data Augmentation for More Training Data

- Generate Ground Truth by Manually Labelling
- Randomly Apply Rotation, Translation and Scaling to Generate More Training Data
- □ Even Better then Manually Labeled Data: 100% Correct

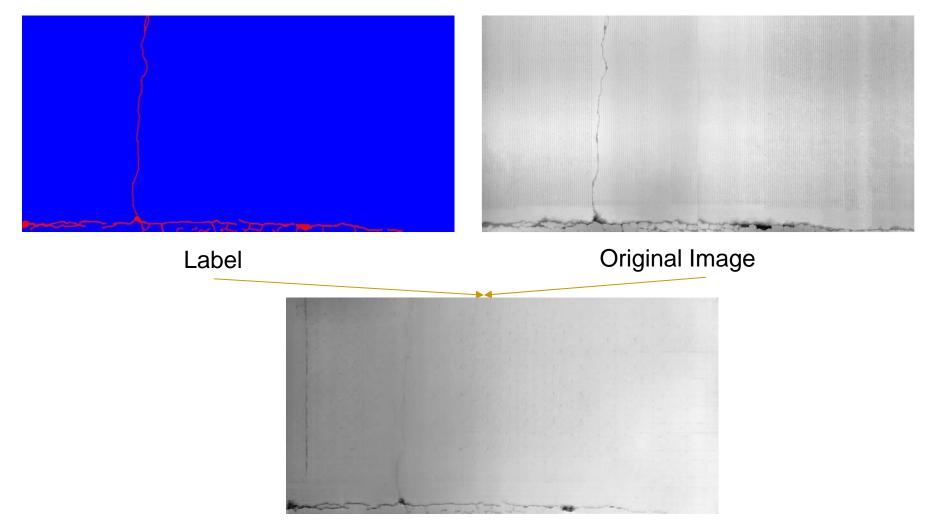


Data Augmentation via Generative Models

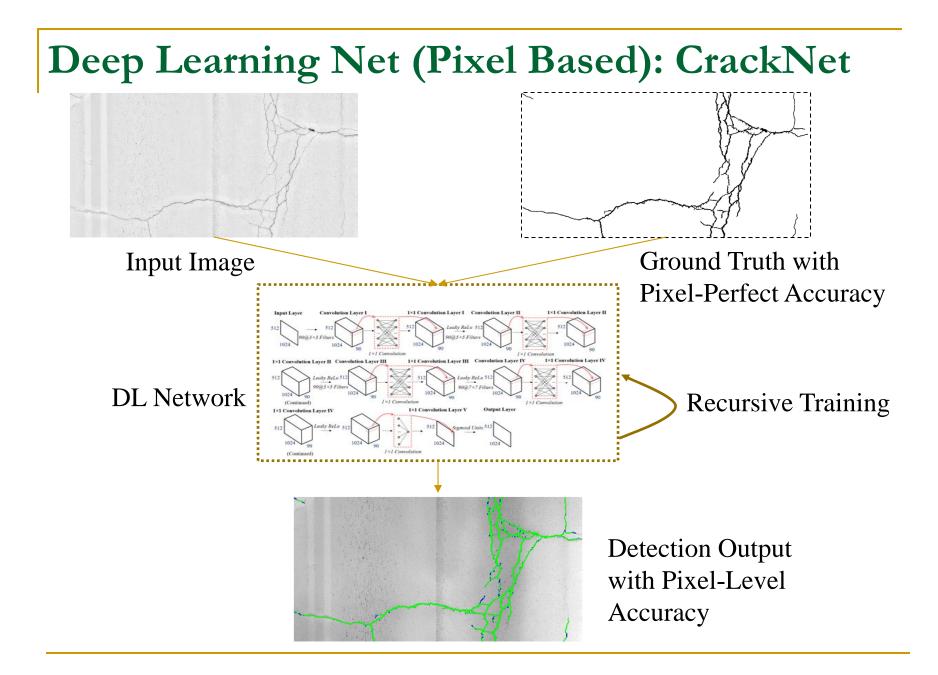


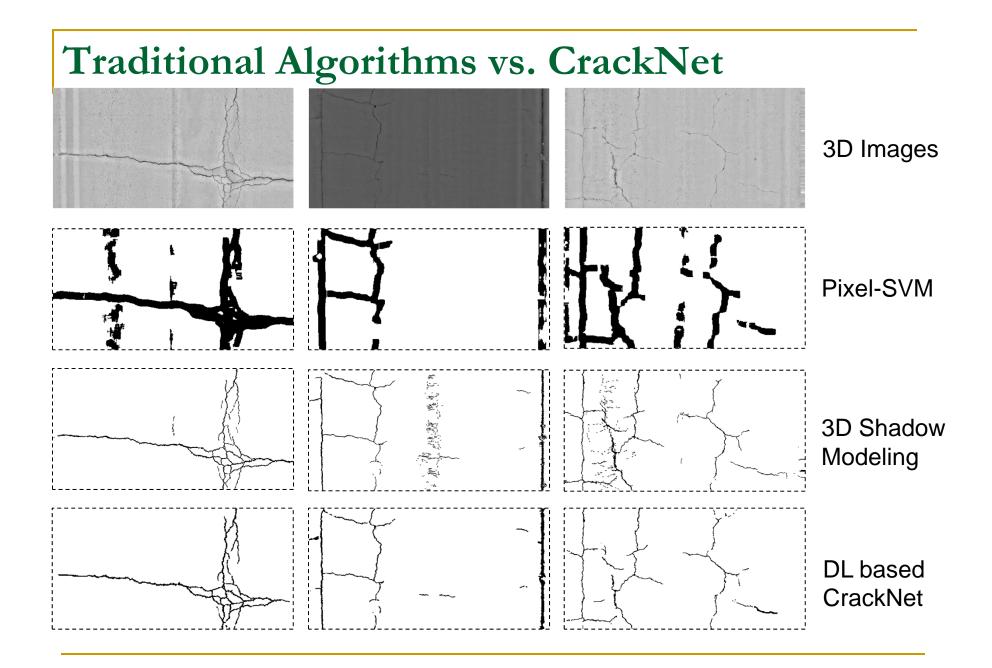
Artificial Image Generated via Generative Adversarial Networks (GAN)

Data Augmentation via Generative Models

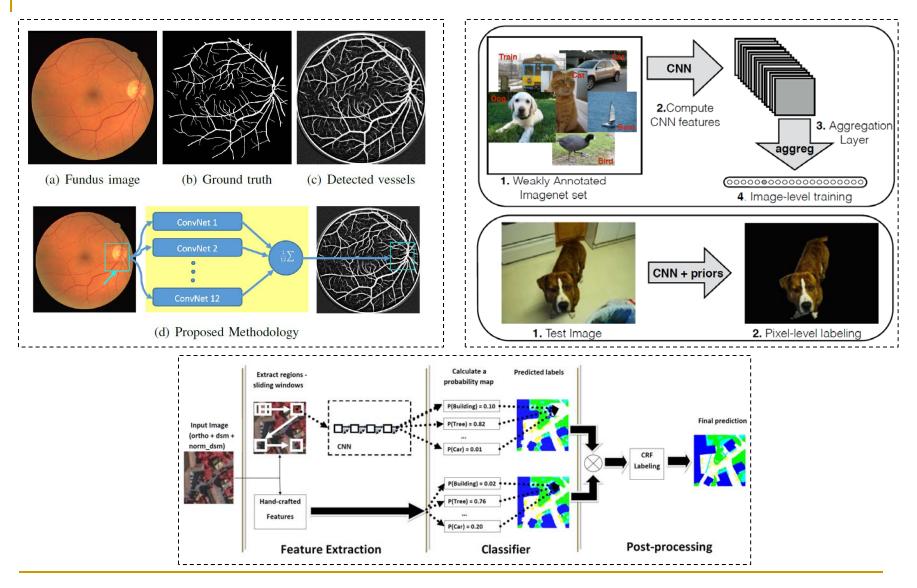


Artificial Image Generated via Generative Adversarial Networks (GAN)

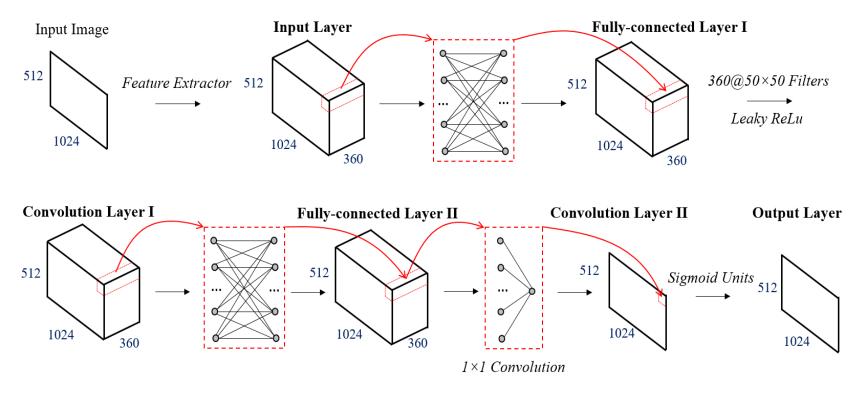




Pixel-Level CNN

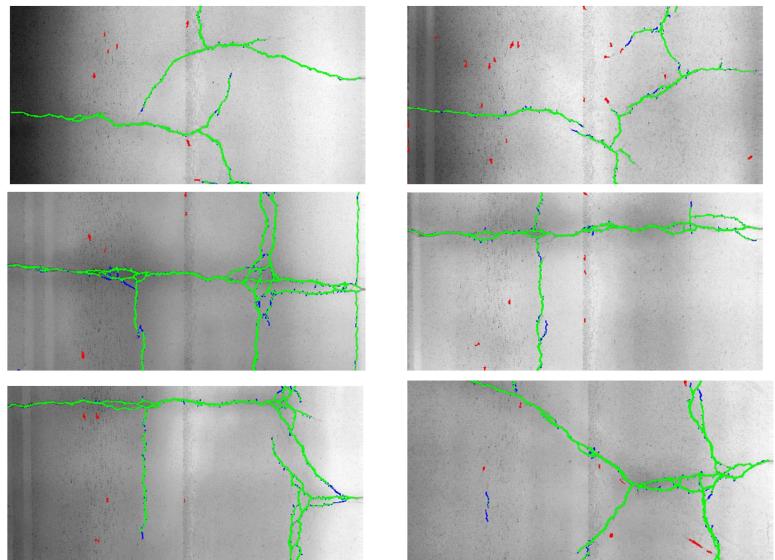


CrackNet for Pixel-Level Accuracy

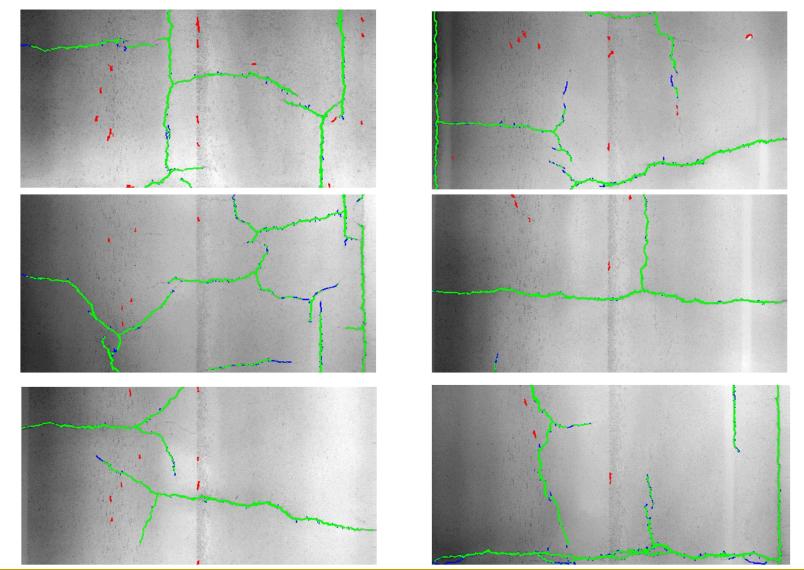


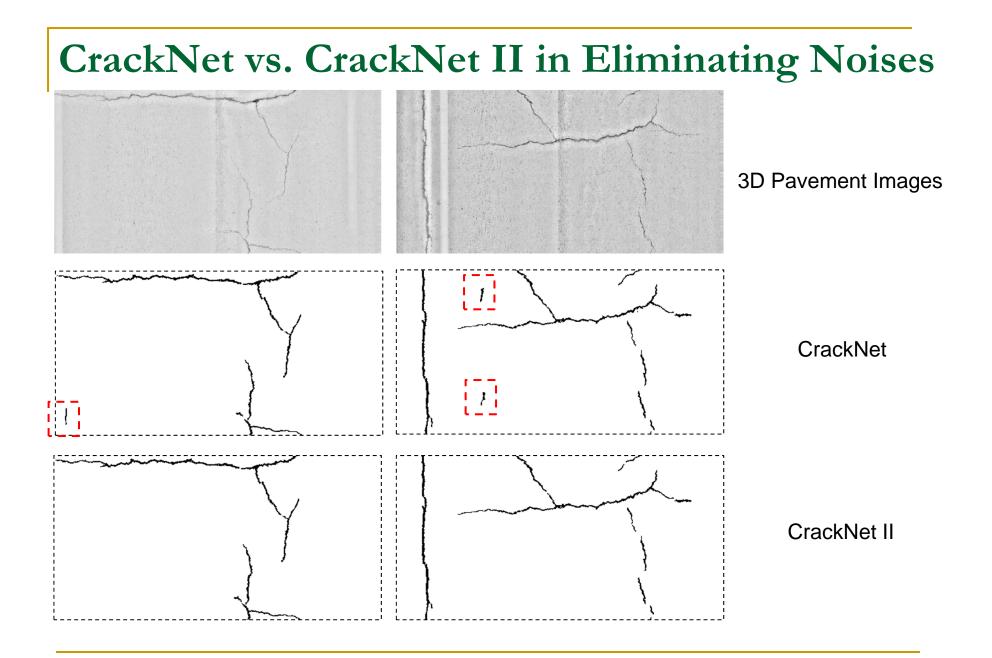
- **7** Layers
- **1**,159,561 Parameters

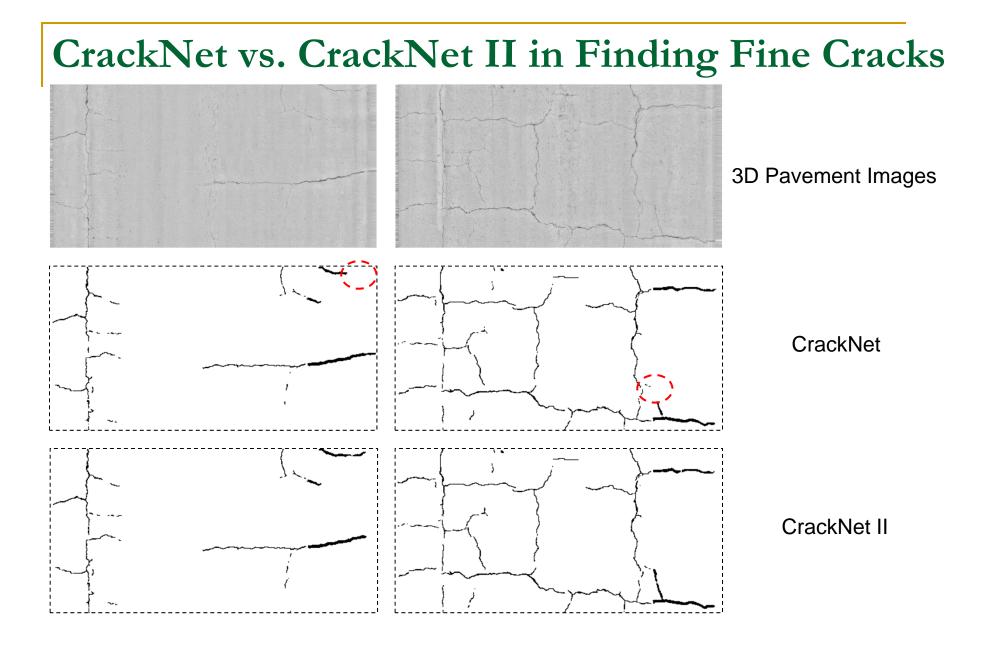
Performance

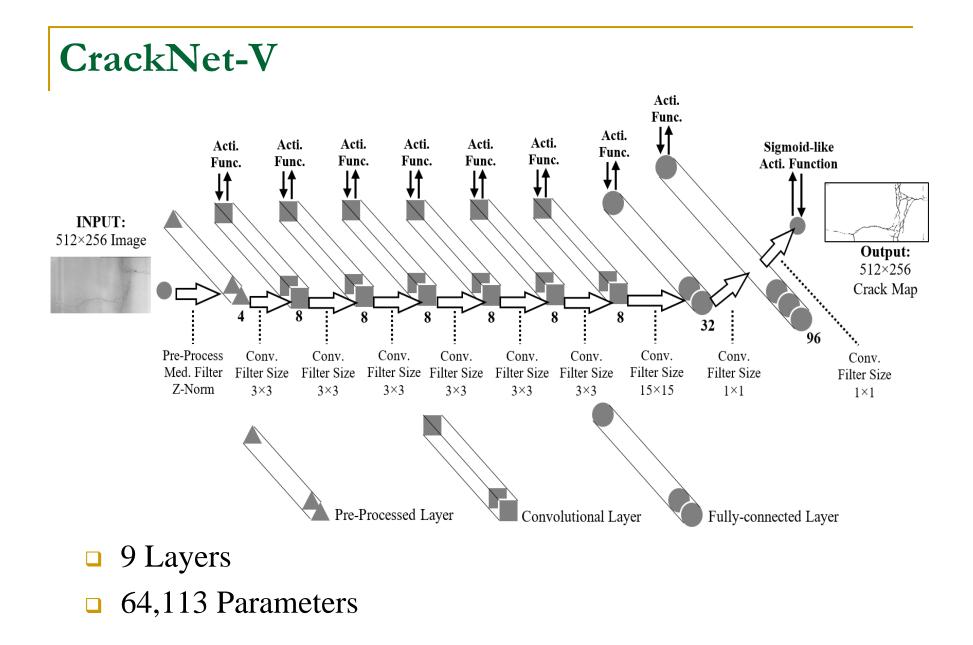


Performance

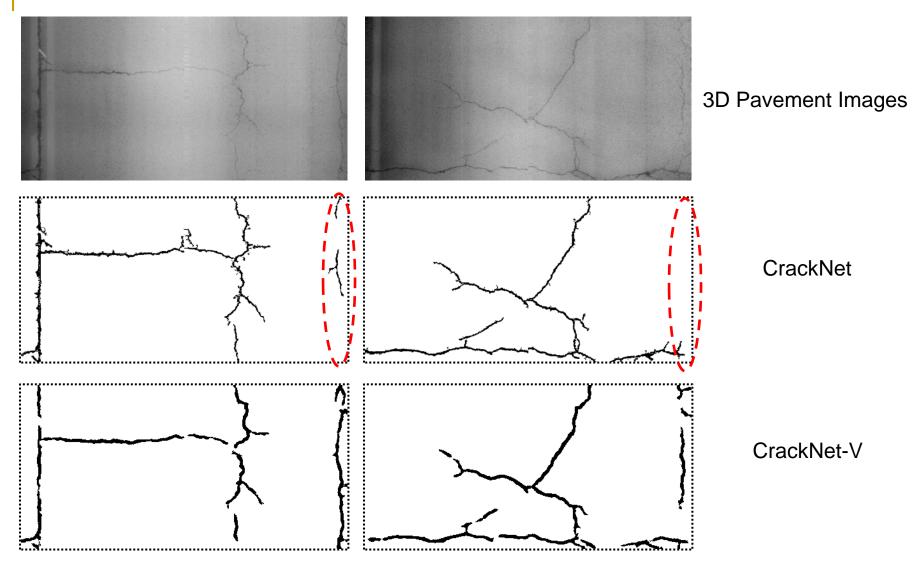




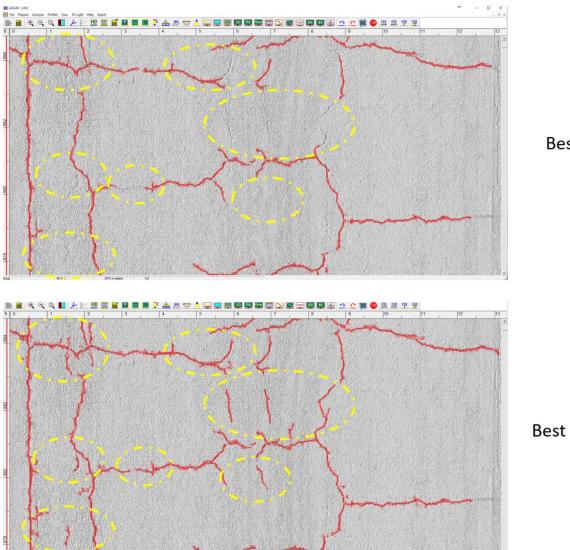




Performance of CrackNet-V



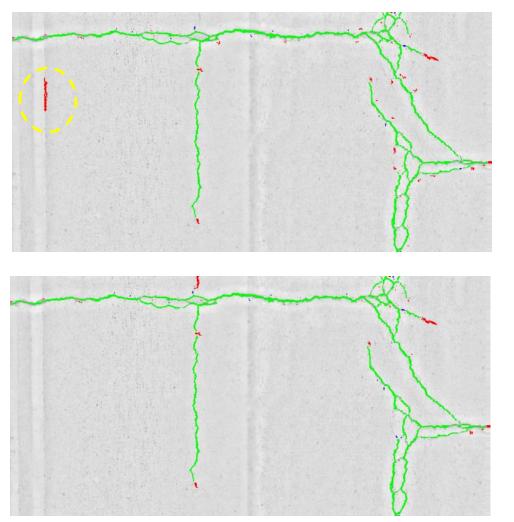
Recurrent Neural Network for Crack Detection



Best CrackNet

Best CrackNet + RNN

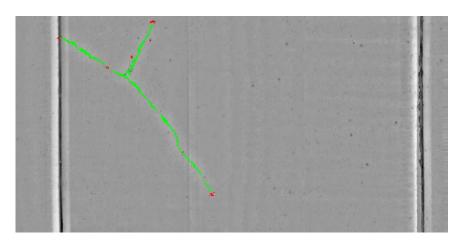
Recurrent Neural Network for Crack Detection

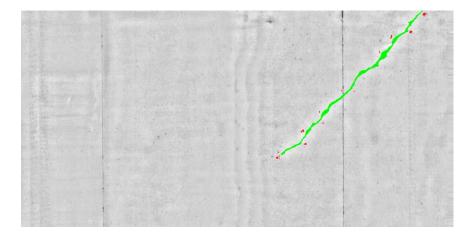


Best CrackNet

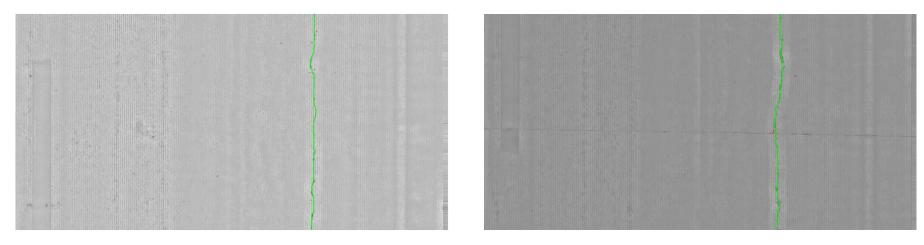


CrackNet on Rigid Surfaces





Jointed Surface



Grooved Surface

Critical Advantages of CrackNet (All Versions)

- Consistency of Precision and Accuracy
 - Different Types of Pavements in Various Conditions
- □ 90% Precision & Recall: All the Time!
 - □ False Positives, False Negatives < 10%
- □ Training of DL Networks: Cumulative
 - Similar to True Learning Process by Humans
- No Need of Tuning Parameters for Different Pavement Surfaces
 - Once Working, Always Working for Any Pavements without Human Intervention

Future Work

□ Image Library for Training, Never Ending

- More Labeled 3D & 2D Pavement Images in Library
- Variations of Pavement Distresses
- > Artificial Training Data through Augmentation
- Long-term Training & Optimization
 - Field Tests (Diversified Data) for AI Net Optimization
- Self-Taught Learning
 - Unsupervised Learning from Unlabeled Data
- Real-time Application
 - Massively Parallel Computing in a Single Workstation
 - > >200MPH Post-Processing?

Conclusions

- Limitations of Traditional Automated Algorithms
 - Inconsistency & Substantial Manual Intervention
- Deep Learning (DL) Based Networks/Solutions
 - Strong capabilities of learning from experiences: cumulative
 - Consistent precision and bias level on various roads
- DL-based Automation with Pixel-Level Accuracy
 - Ready for Production; Continuing for Knowledge Accumulation
- □ Future: AI/DL is the clear choice!
 - > Implementations and Refinements
 - Non-Cracking Distresses
 - Large team: challenge on resources
 - Rail, Tunnel et al

CrackNet:

The New Generation

