Performance of Fully Automated 3D Cracking Survey with Pixel Accuracy based on Deep Learning

Kelvin C.P. Wang

Oklahoma State University and

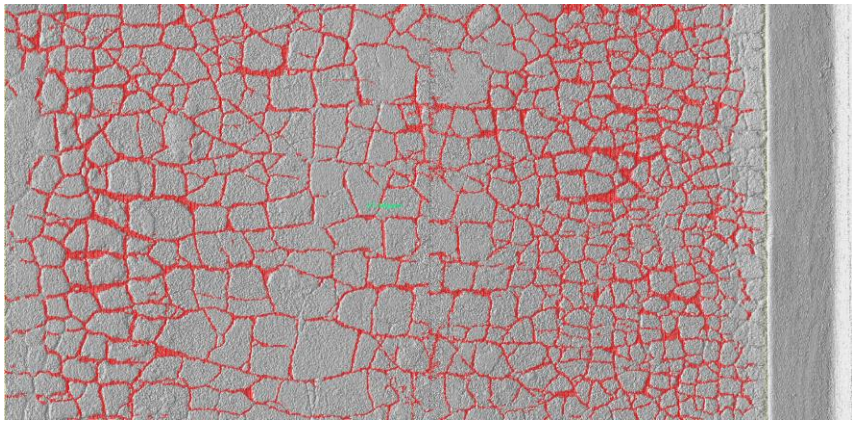
WayLink Systems Corp.

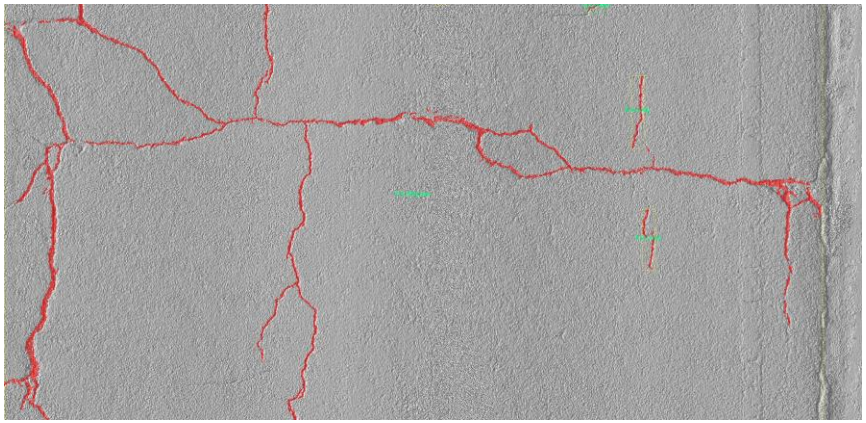
2017-10-19, Copenhagen, Denmark

European RPUG

Objectives

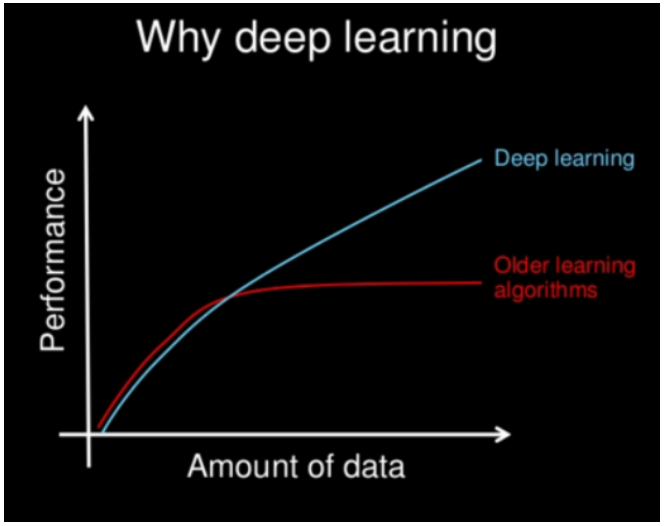
- Automated Crack Detection
  - Find the Actual Location of Distresses with Pixel-Perfect Accuracy
- Automated Crack Classification
  - Label Distress Types





Deep Learning

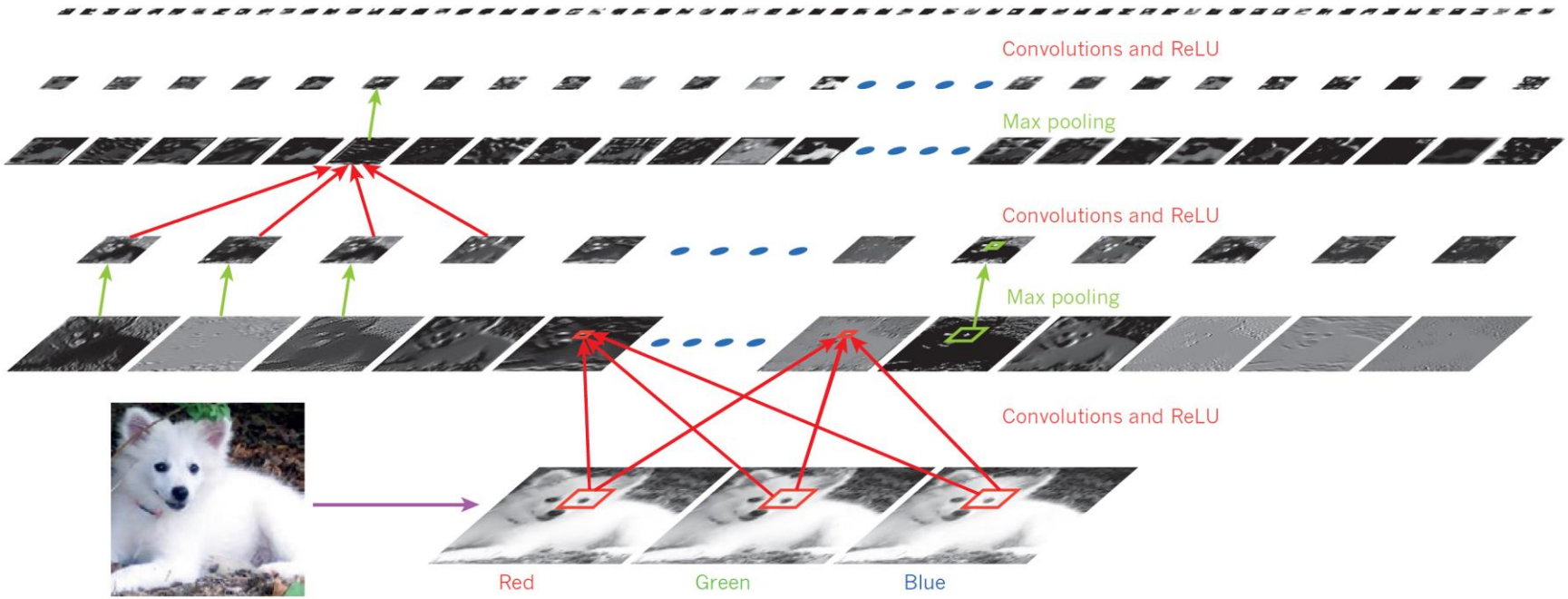
- Strong Learning Ability
  - Learning from Experiences
  - Exploiting Understanding on New and Unlabeled Examples
- Versatility
  - A Deep Learning Network Can Detect Multiple Types of Objects (e.g. Pavement Distresses)
- Enhanced Reliability
  - Feed with Exhaustive Variations of Examples



Deep Learning Application

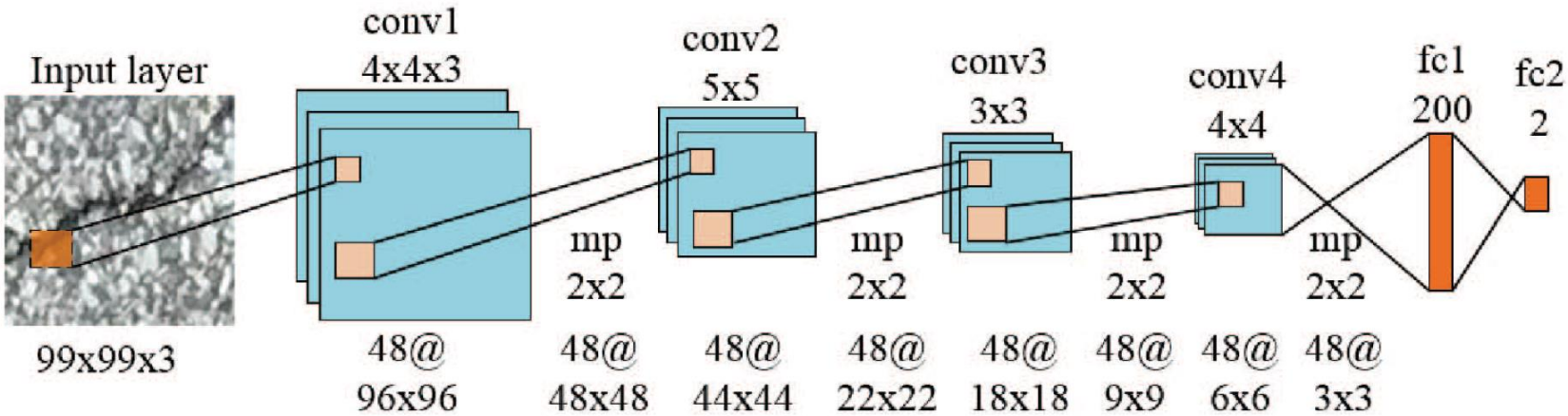
- Self-Driving
  - Human-Car Language Interaction
  - Environment Perception
  - Traffic Condition Handling
- Medical
  - New Drug Toxicity Prediction
  - Lung Cancer Diagnosis
- Financial
  - Face-Detection-Based Payment Systems
  - Stock Prediction
- Games
  - DeepMind Alpha-Go on Board Game
  - OpenAI Universe on Computer Game

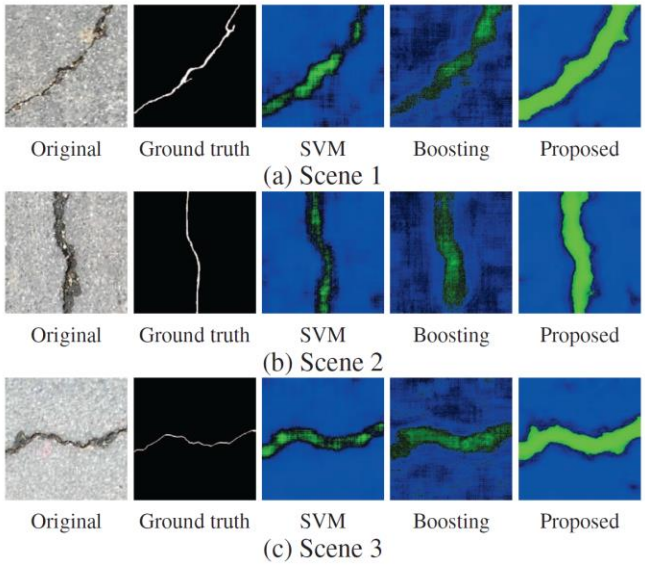
Structure Characteristics of CNN



- Sharing Weights
- Locally-Connected
- Space-Invariant
- Convolution Layer, Max-Pooling Layer, ReLU Layer, Fully-Connected Layer
- Lack of Pixel-Perfect Accuracy

CNNs for Cracking Detection (Cell Image)

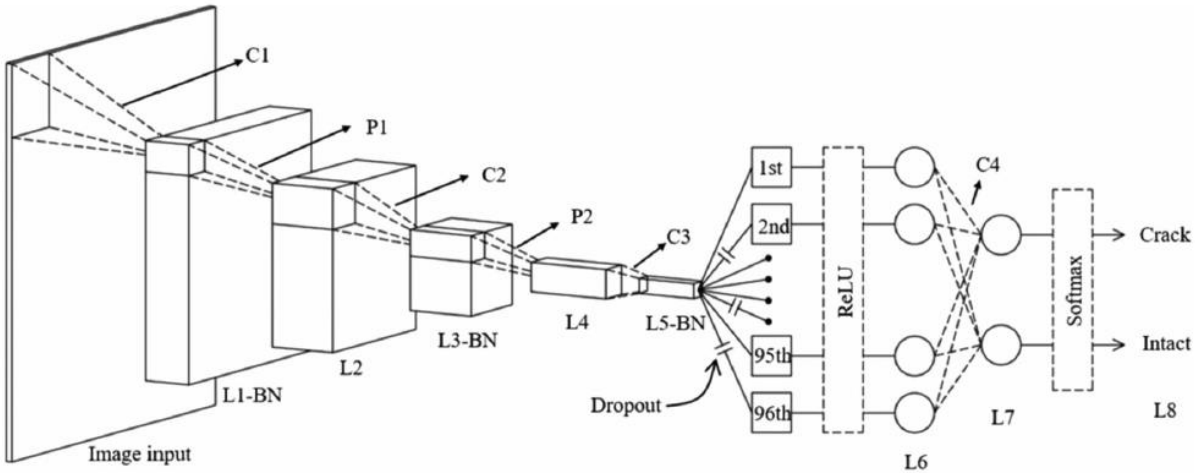


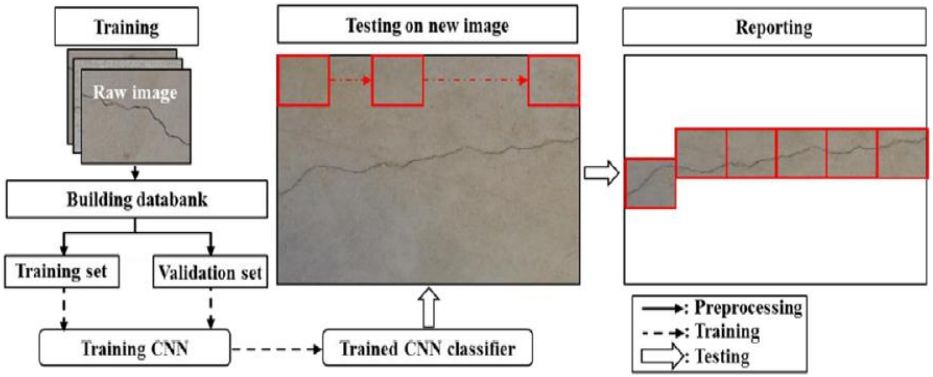


- Images taken by cell phone
- Training Data are limited (500 images)
- Lack of Pixel-Perfect Accuracy

Road Crack Detection Using Deep Convolution Neural Network, *IEEE International Conference on Image Processing, 2016*

CNNs for Cracking Detection (Cell Image)

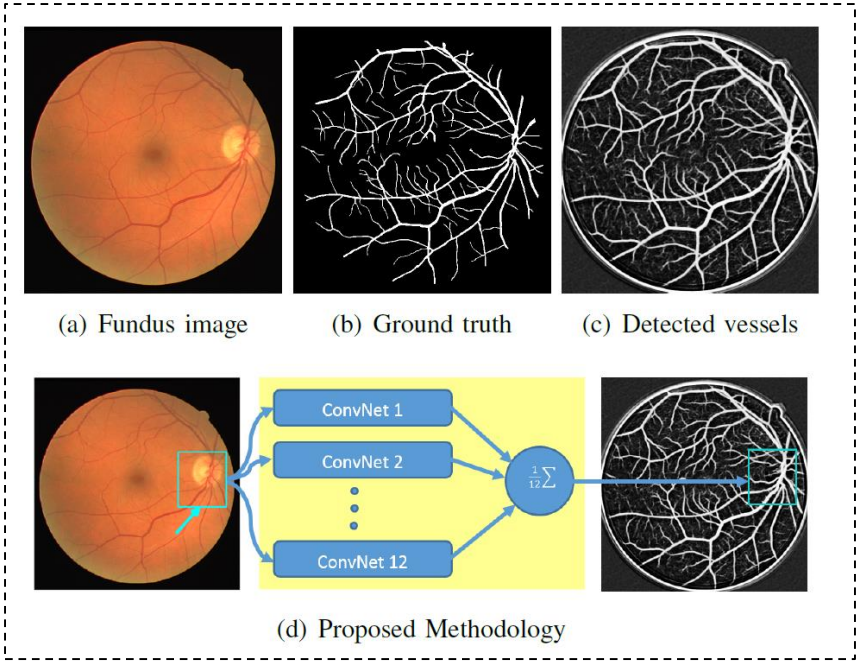




- Detect Cracks in Image Cells
- Training Data are limited (550 images)
- Lack of Pixel-Perfect Accuracy

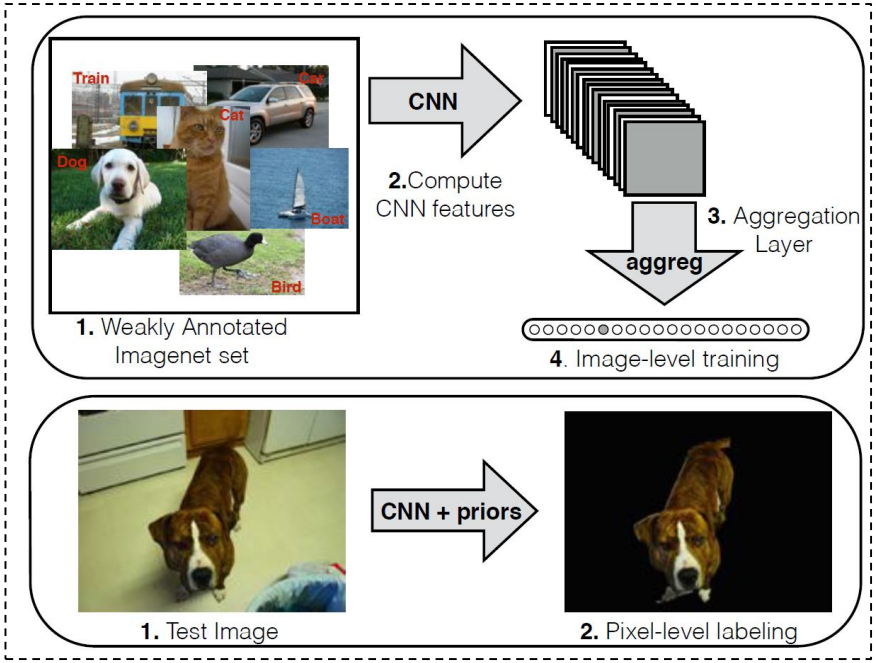
Deep Learning-Based Cracking Damage Detection Using CNNs, *Computer-Aided Civil and Infrastructure Engineering, 2017*

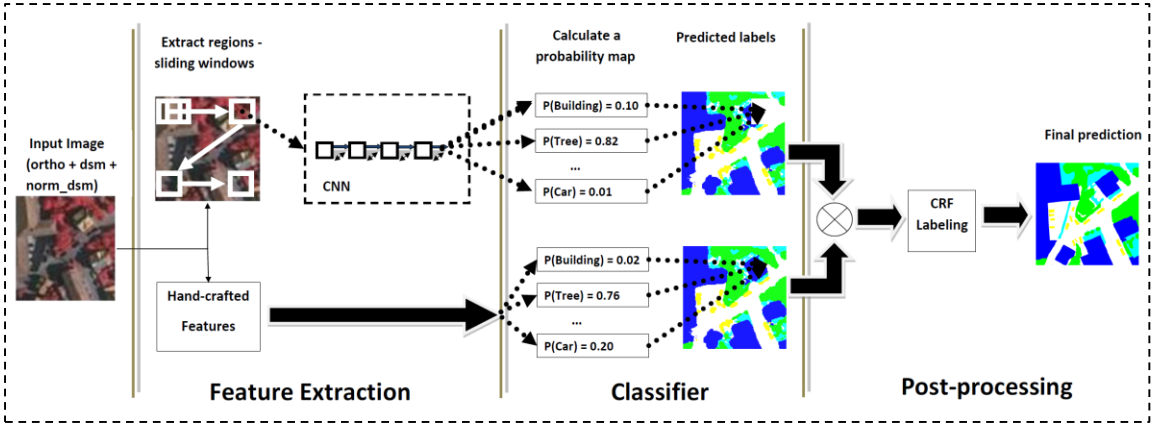
Pixel-Level CNN



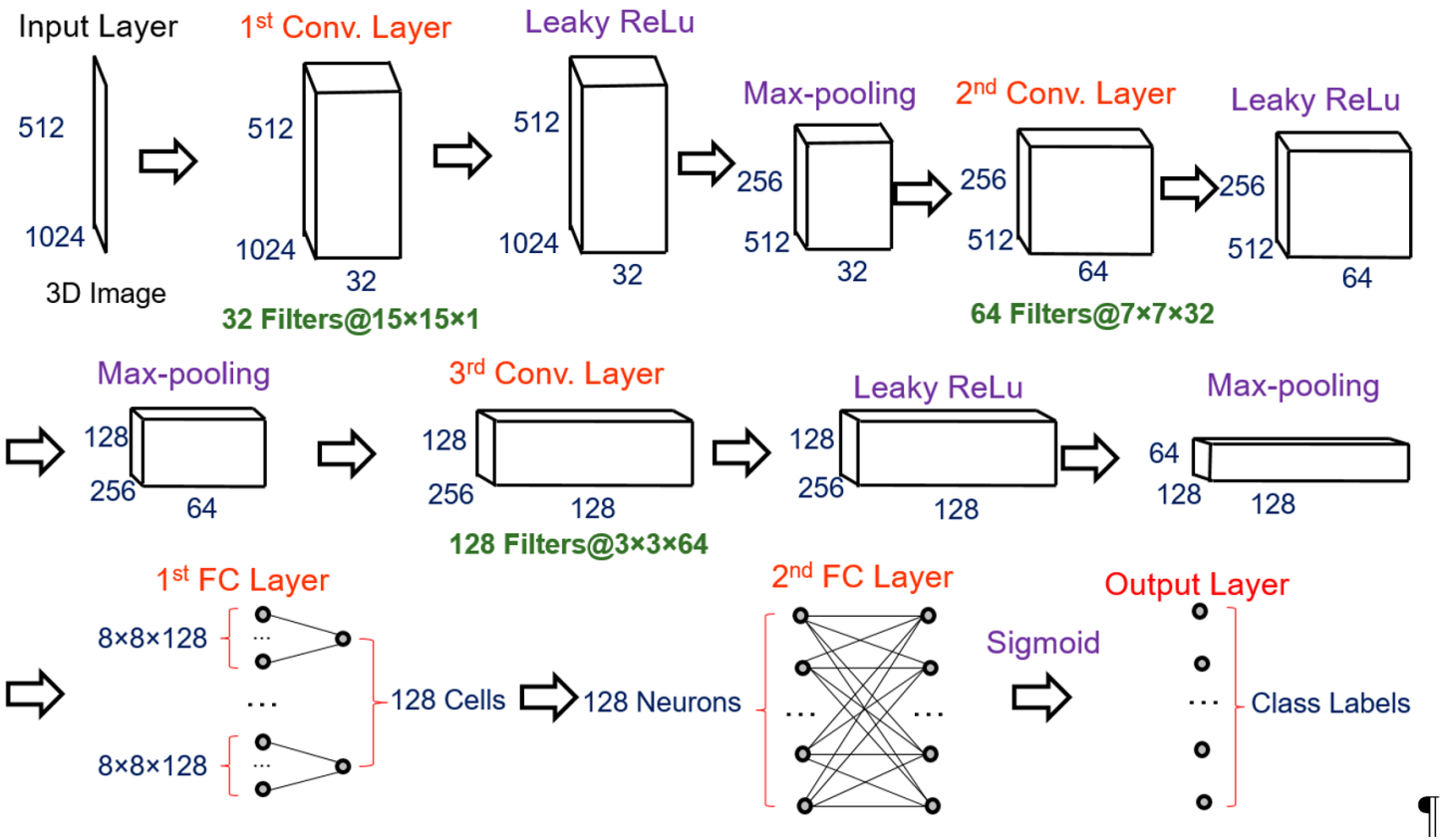
(a) Fundus image (b) Ground truth (c) Detected vessels

(d) Proposed Methodology





CNN by OSU/WayLink Team (Cell Image)

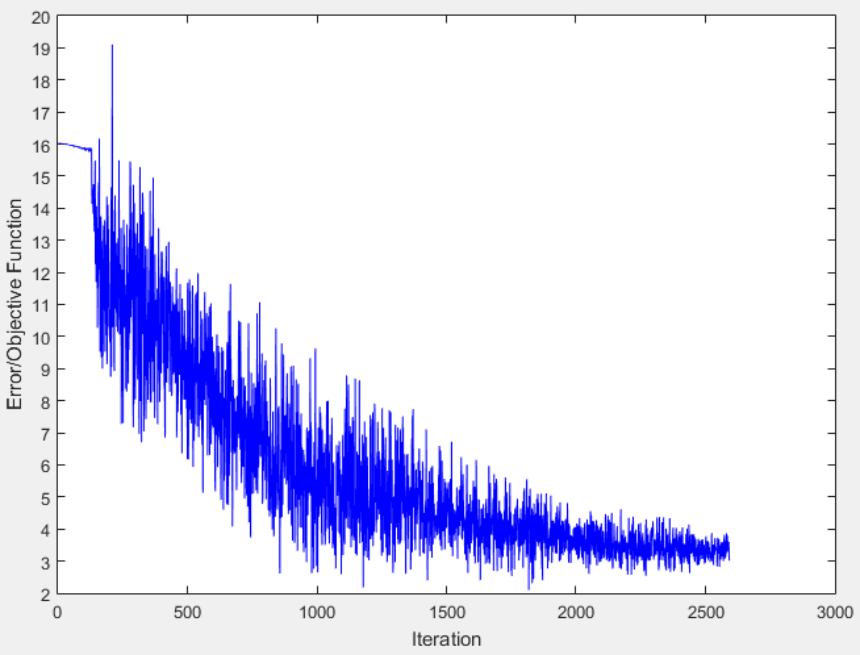


- 11 Layers
- 1,246,496 Parameters

Training

- Recognition Accuracy > 96%

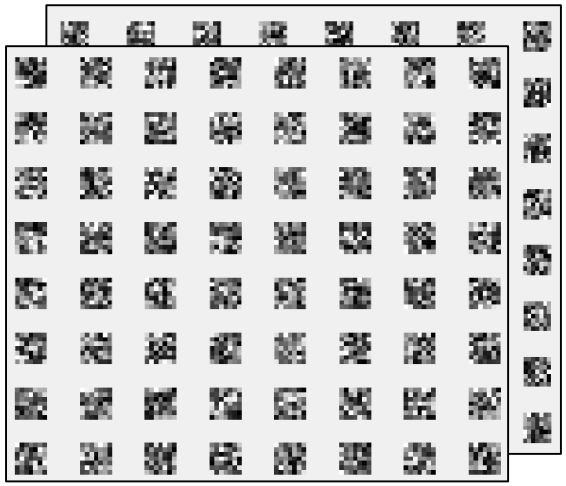
# of Samples	# of Samples with False-positive Errors	# of Samples with False-negative Errors	False-positive Error	False-negative Error	Accuracy
23,296	163	684	0.7%	2.936%	96.364%



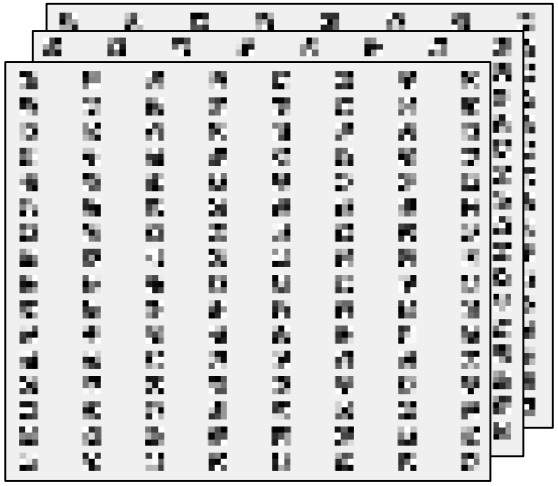
Error Curve

Learned Filters

1st Convolution Layer
32@15×15×1

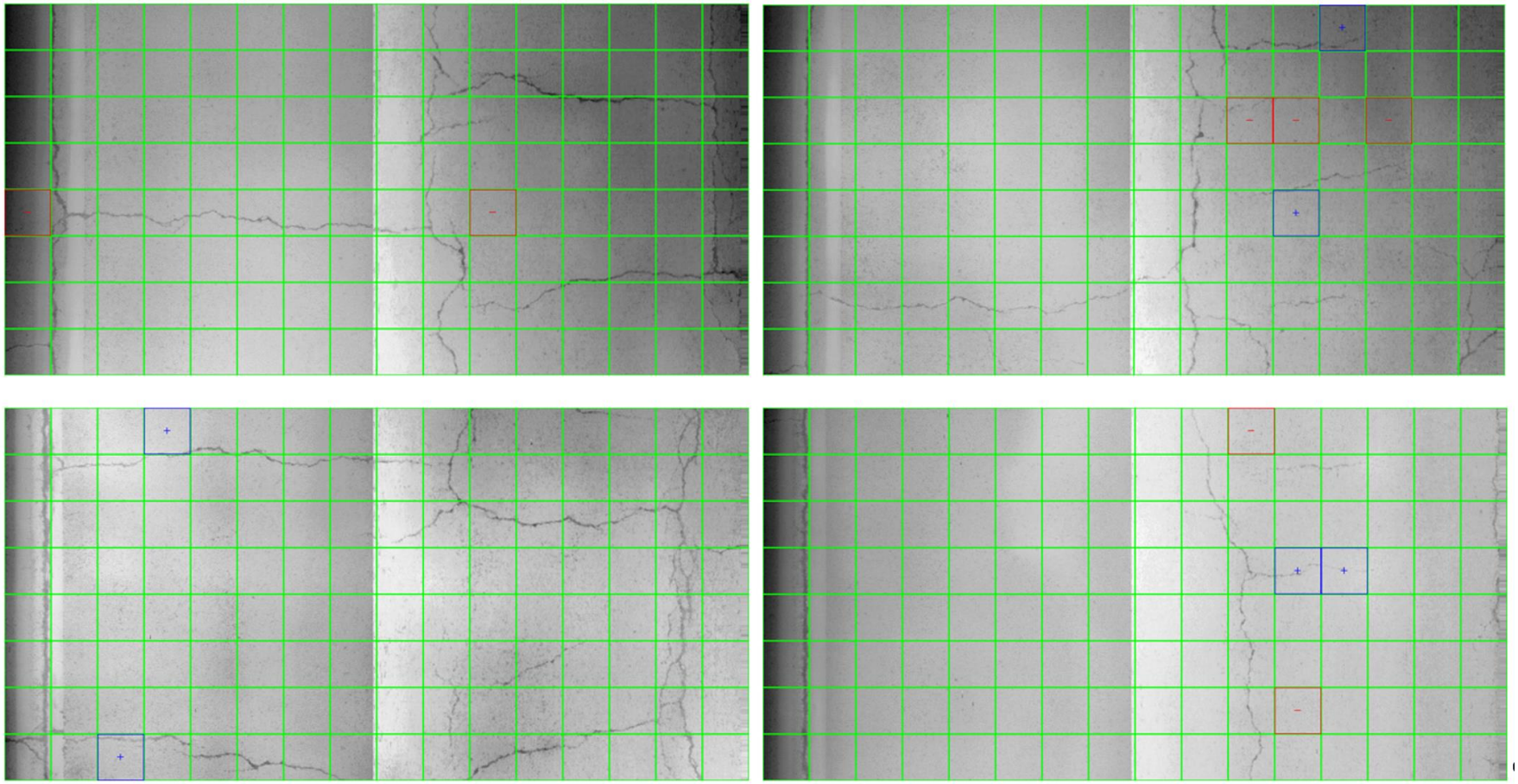


2nd Convolution Layer
64@7×7×32

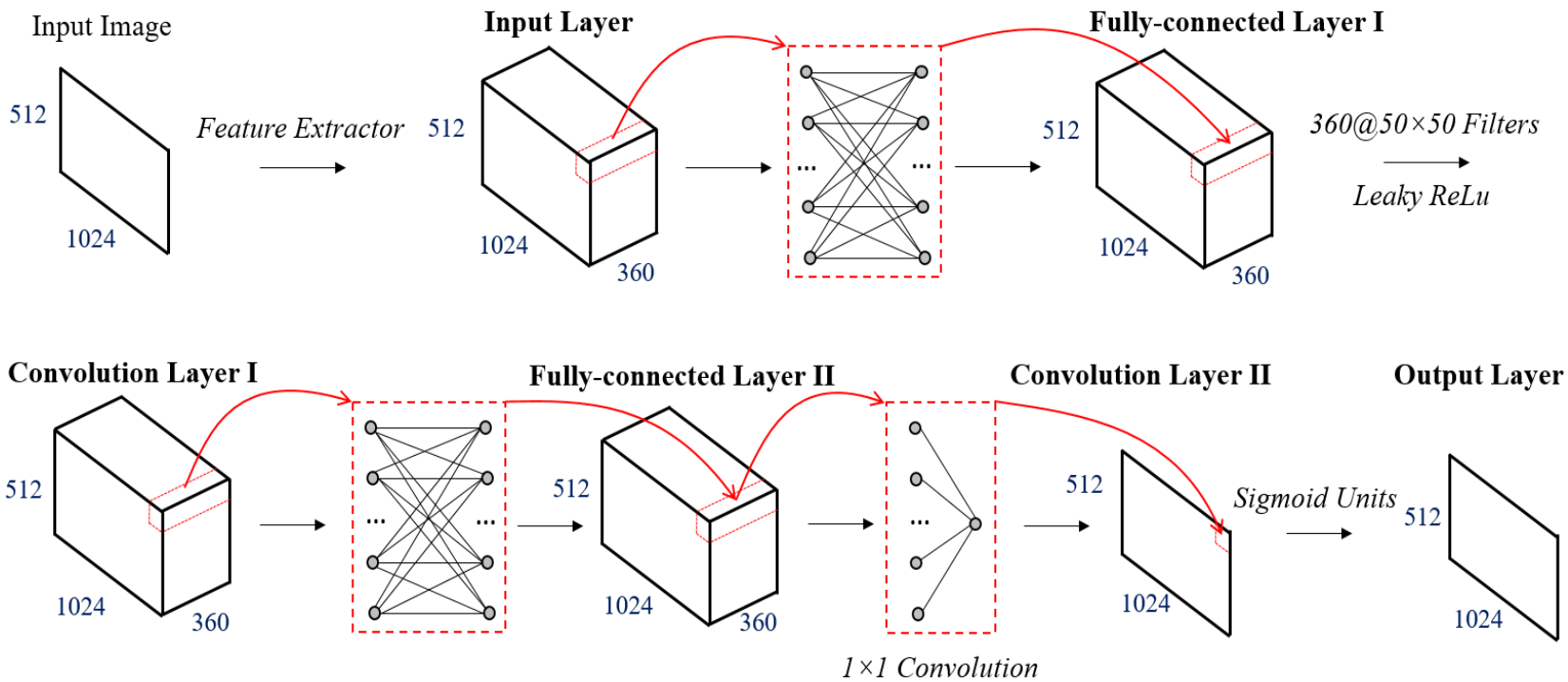


3rd Convolution Layer
128@3×3×64

Testing

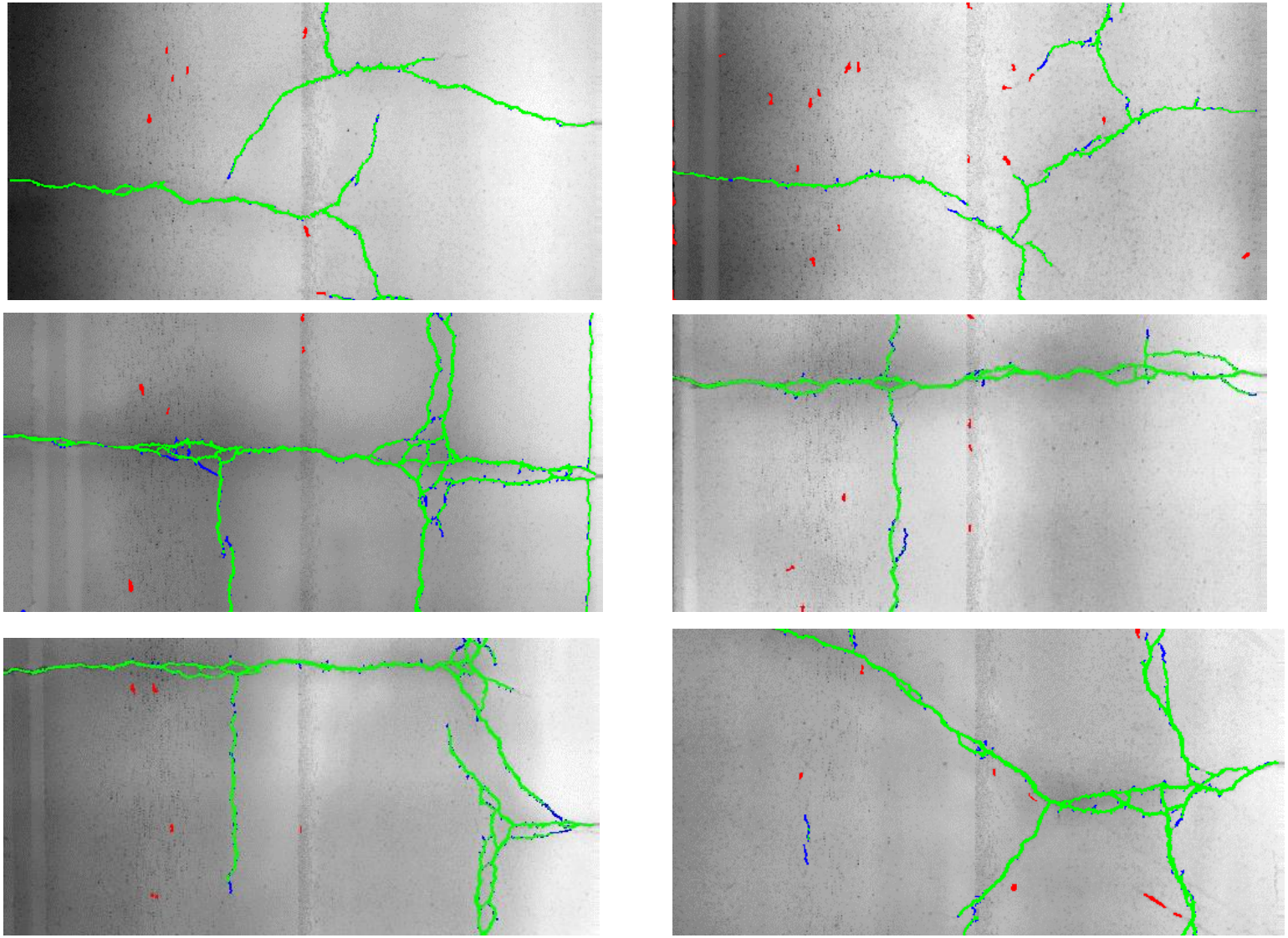


CrackNet for Pixel-Level Accuracy

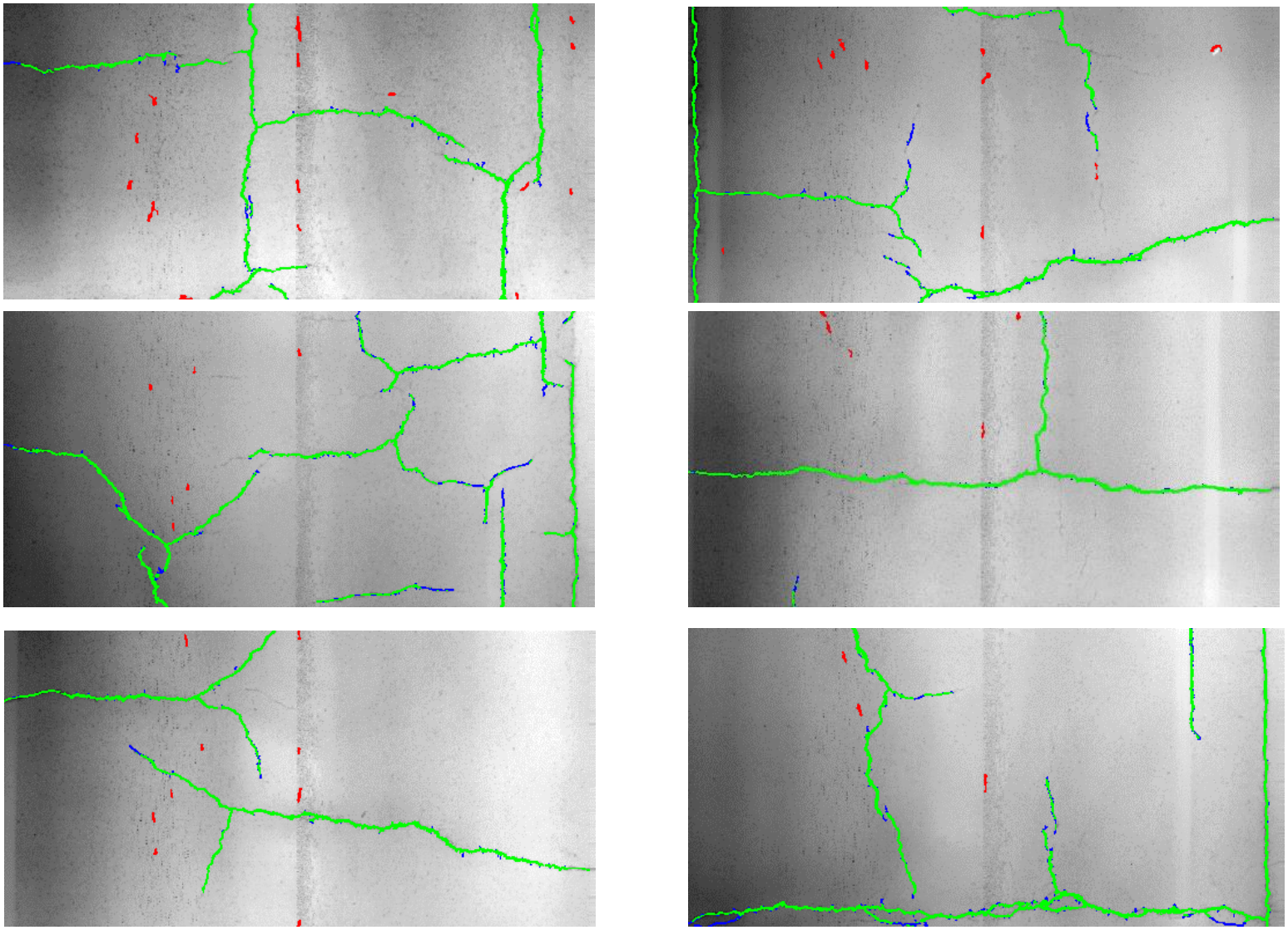


- 7 Layers
- 1,159,561 Parameters

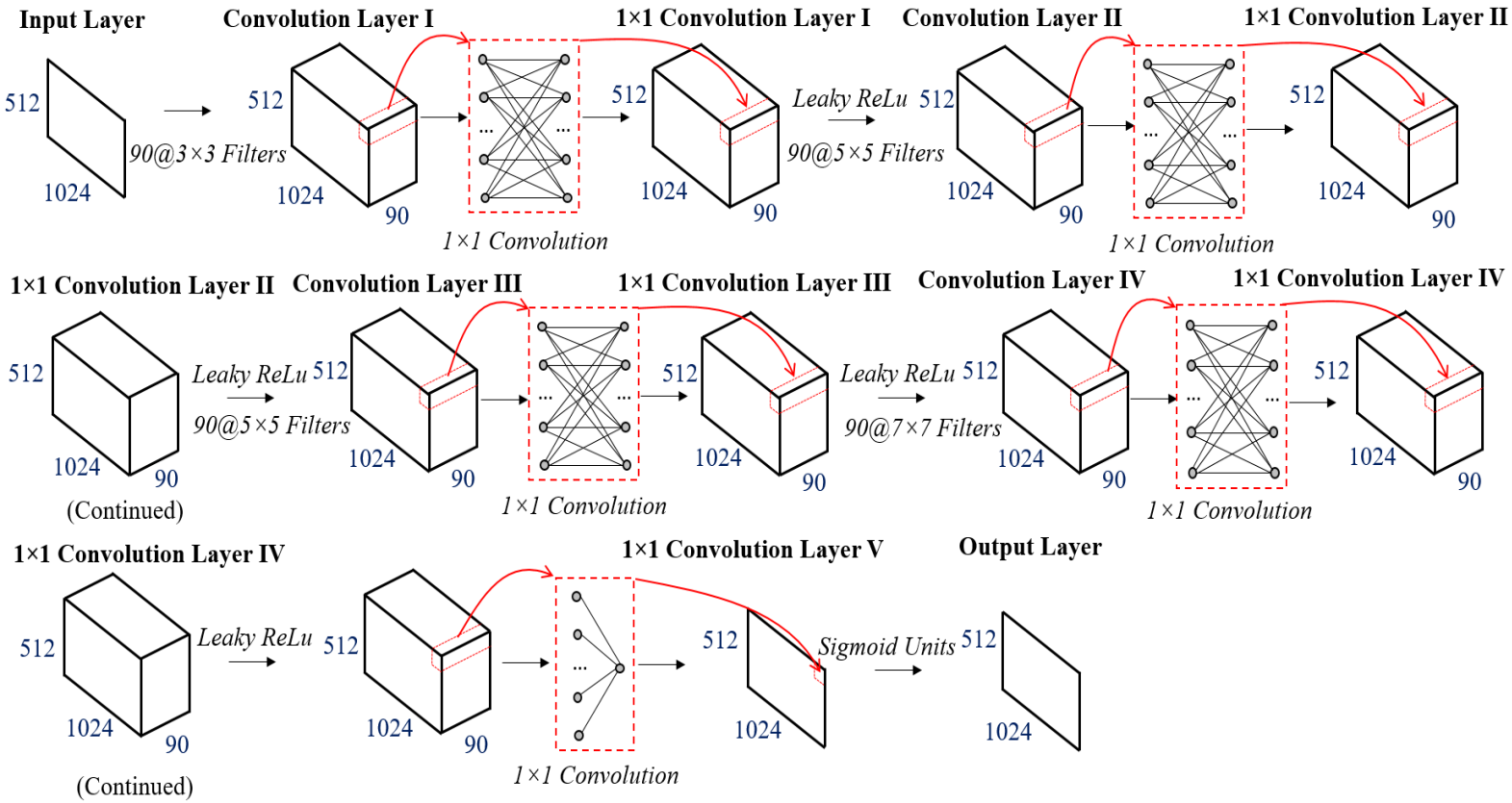
Performance



Performance



CrackNet II

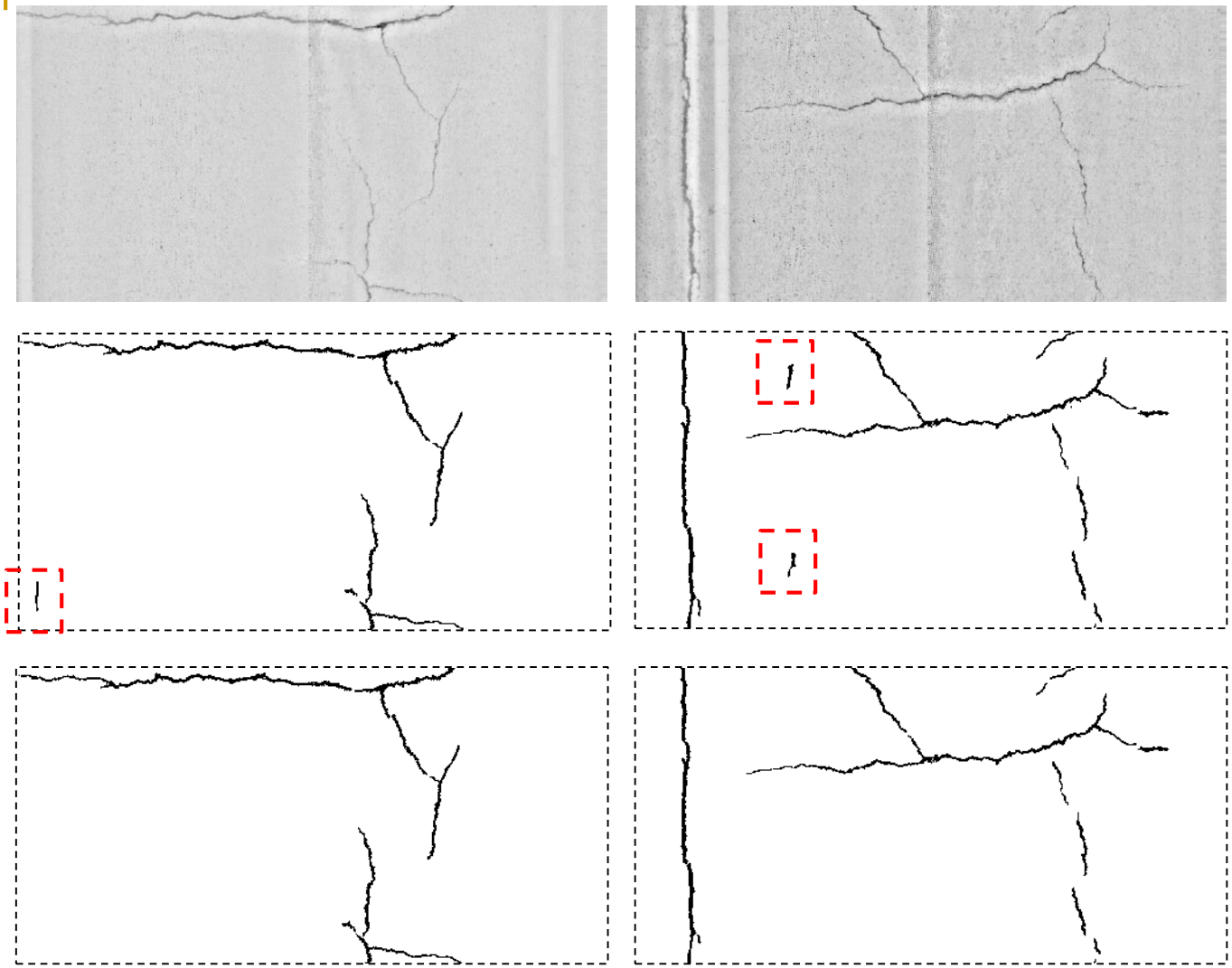


- 10 Layers
- 42,571 Parameters

Advantages of CrackNet II over CrackNet

- Deeper Architecture
  - CrackNet: 5 Layers
  - CrackNet II: 10 Layers
- Enhanced Feature Extraction
  - CrackNet: Handcrafted Features + Learned Features
  - CrackNet II: All Learned Features
- Faster Speed
  - CrackNet II is 5 times faster than CrackNet
- Better Performance
  - Higher Precision (Lower False-Positive Rate)
  - Higher Recall (Lower False-Negative Rate)

CrackNet vs. CrackNet II in Eliminating Noises

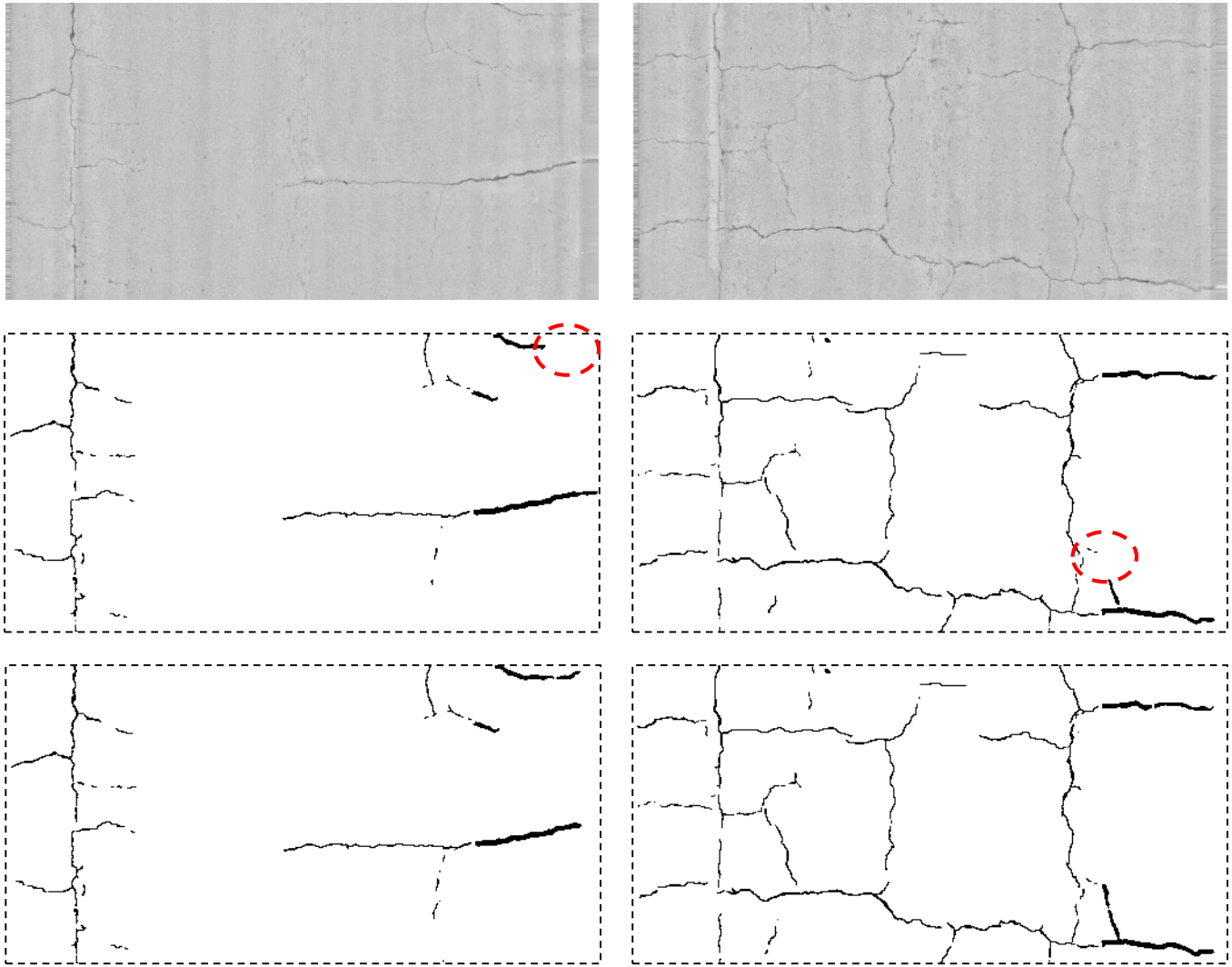


3D Pavement Images

CrackNet

CrackNet II

CrackNet vs. CrackNet II in Finding Fine Cracks

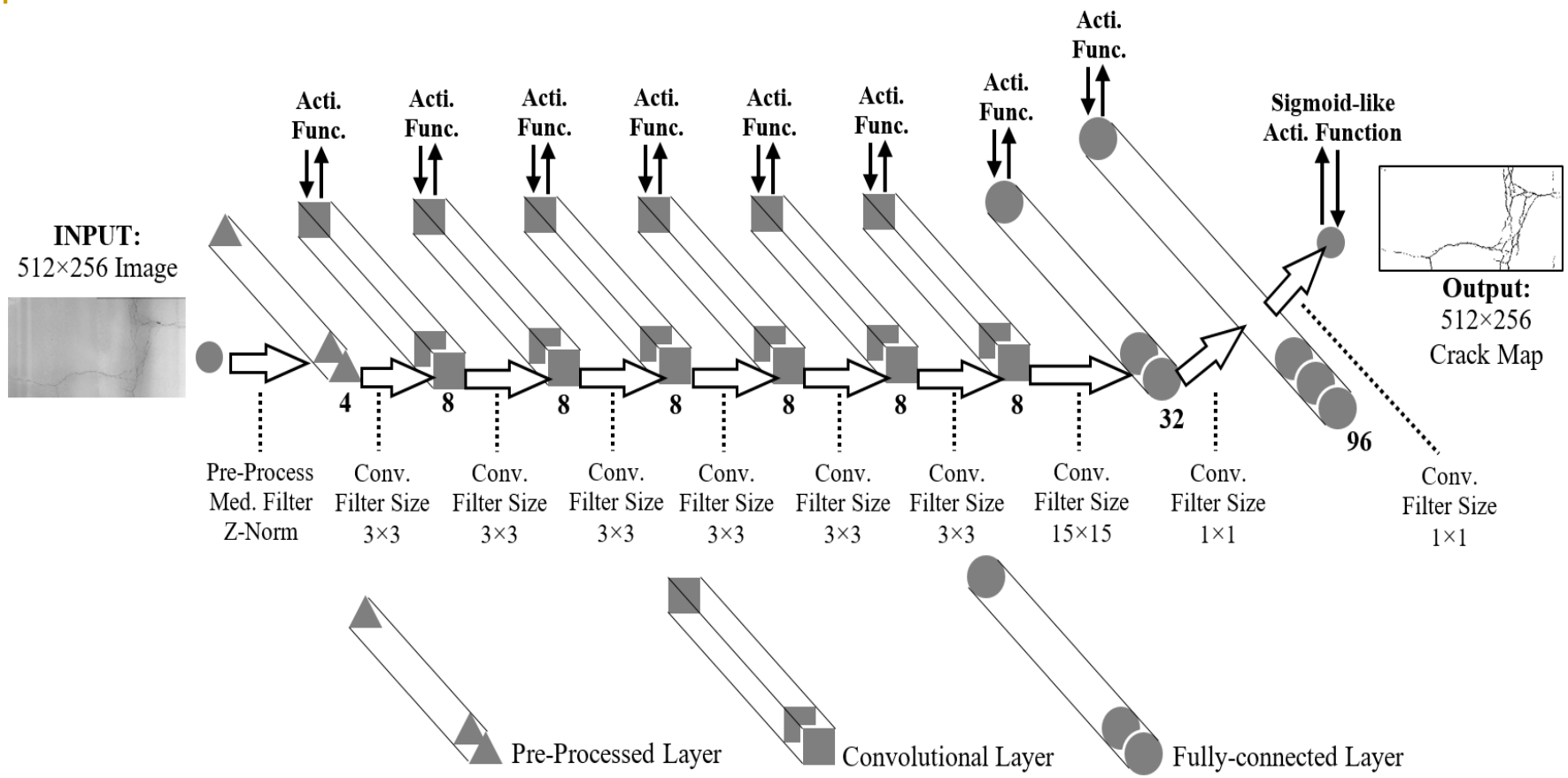


3D Pavement Images

CrackNet

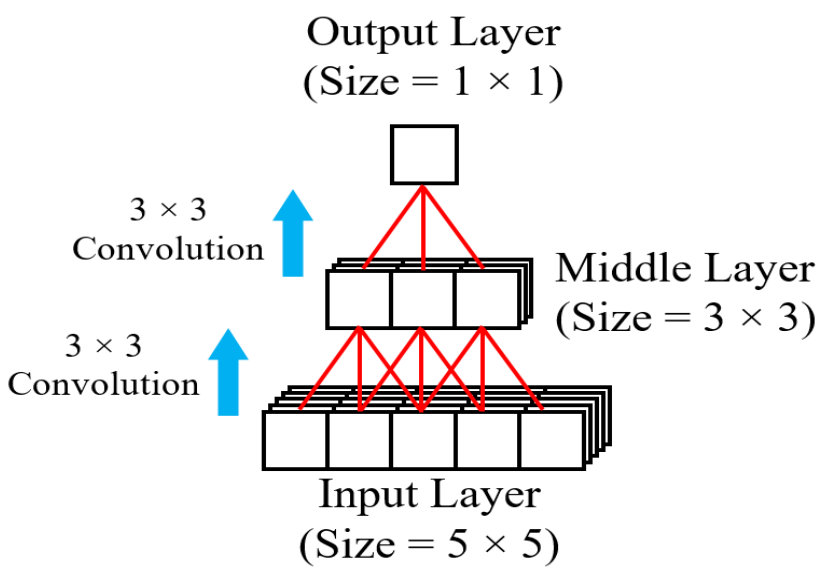
CrackNet II

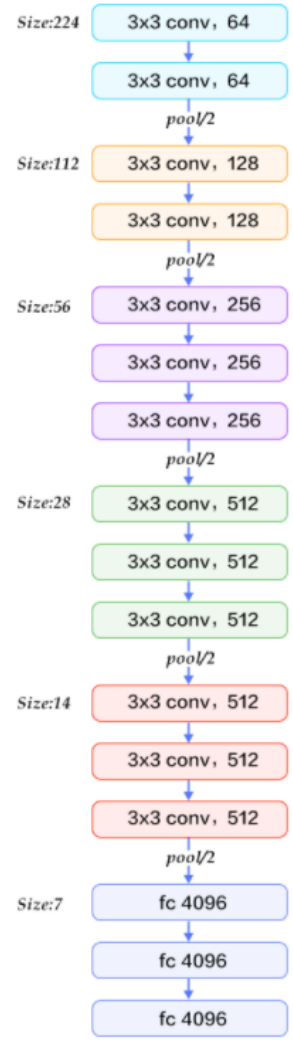
CrackNet-V



- 9 Layers
- 64,113 Parameters

VGG



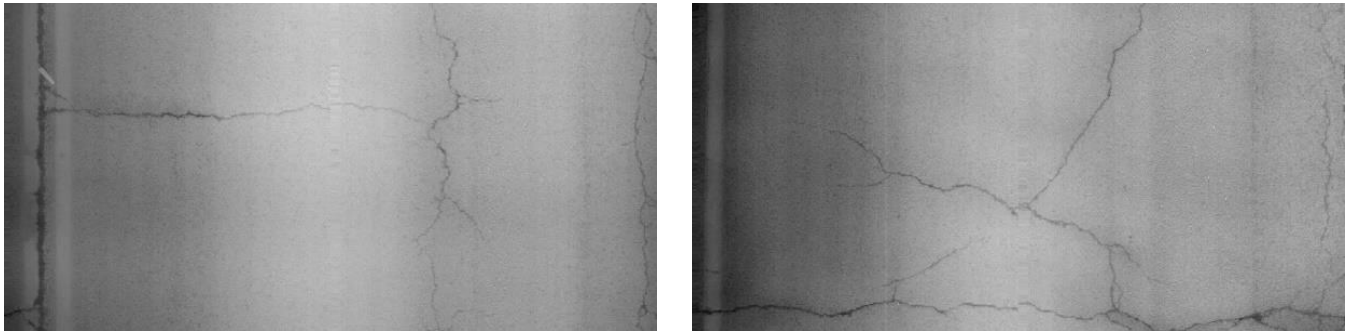


- 3×3 Filters for Convolution Layers
- Stack of Many 3×3 Convolution Layers
- Improved Time Efficiency with Fewer Parameters

Advantages of CrackNet-V over CrackNet

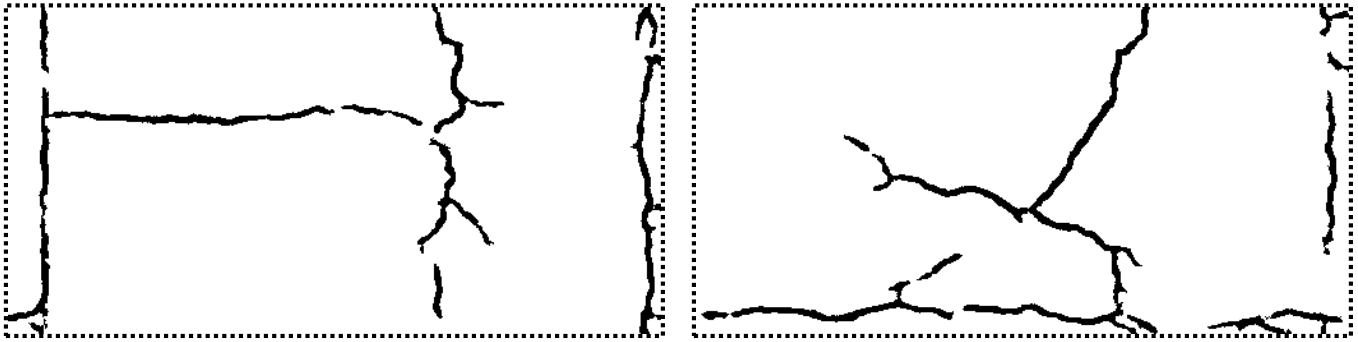
- Deeper Architecture
  - CrackNet: 5 Layers
  - CrackNet-V: 9 Layers
- Robustness in Detecting Fine Cracks
  - CrackNet-V is able to detect more fine cracks
- Faster Speed
  - CrackNet-V is 4 times faster than CrackNet
- Better Performance
  - Significantly Higher Recall (Lower False-Negative Rate)

Performance of CrackNet-V



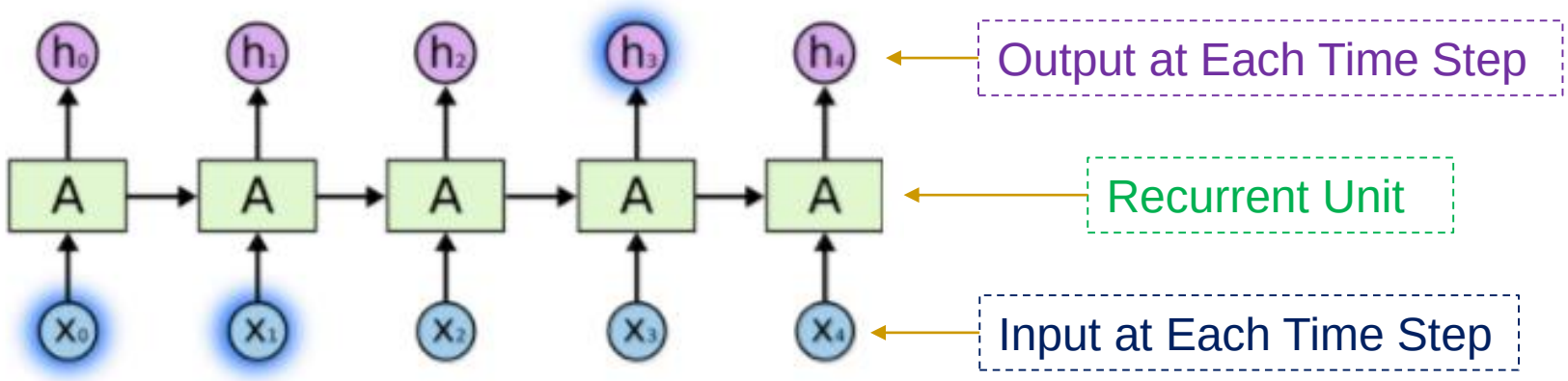
3D Pavement Images

CrackNet



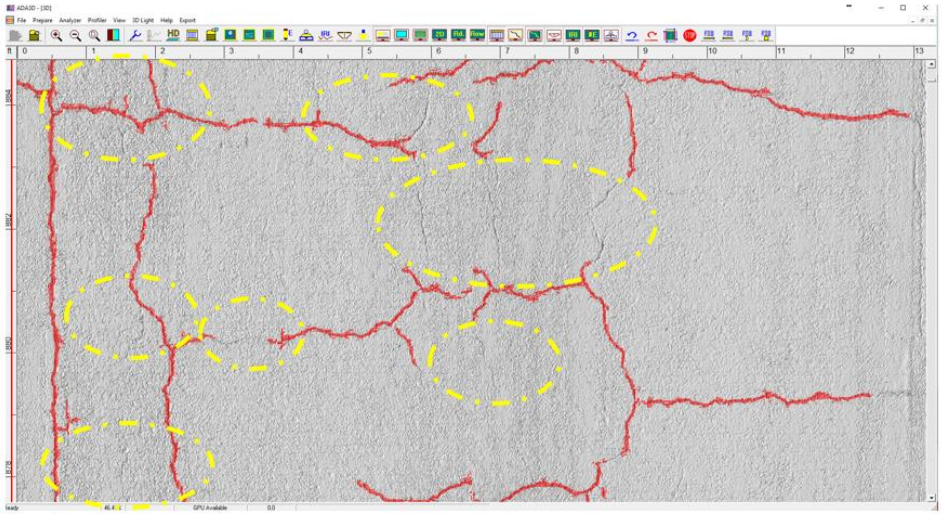
CrackNet-V

Recurrent Neural Network (RNN)

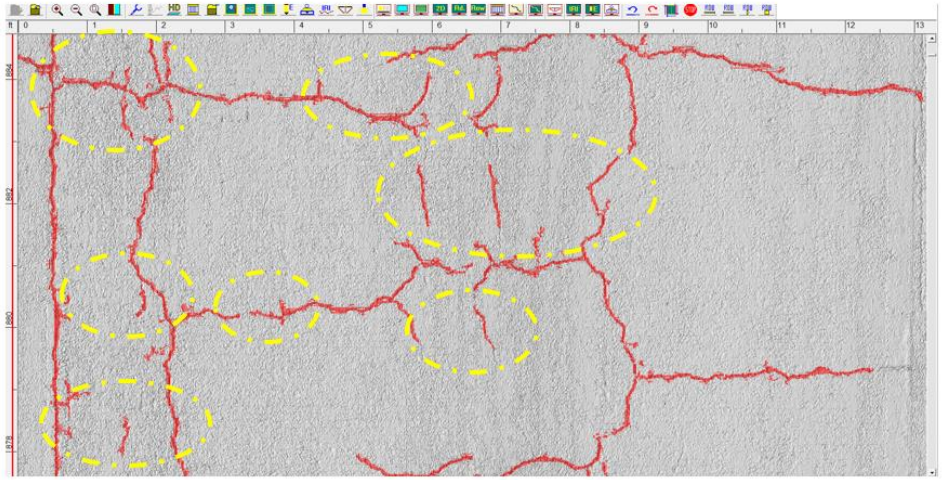


- Sequence Learning
  - Perform Predictions Given Specific Sequences
- Implication for Pavement Crack Detection
  - Pavement Crack: A Sequence of Distinctive Pixels with Unique Features

Recurrent Neural Network for Crack Detection

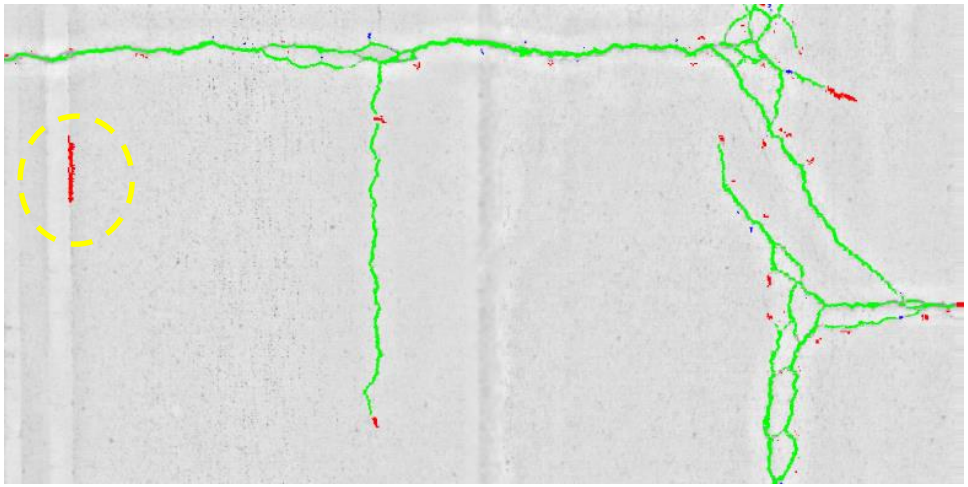


Best CrackNet

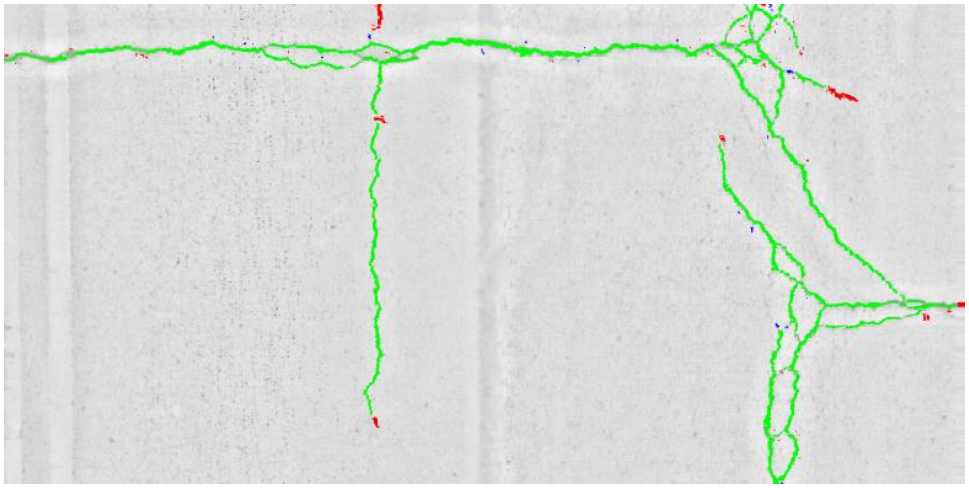


Best CrackNet + RNN

Recurrent Neural Network for Crack Detection

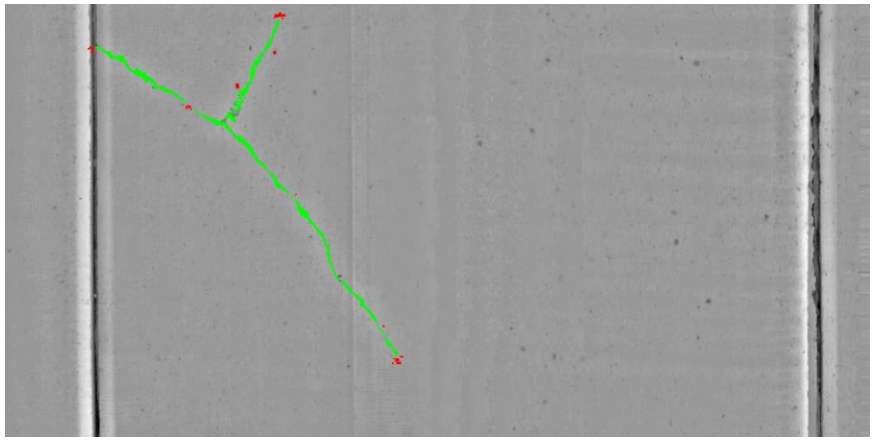


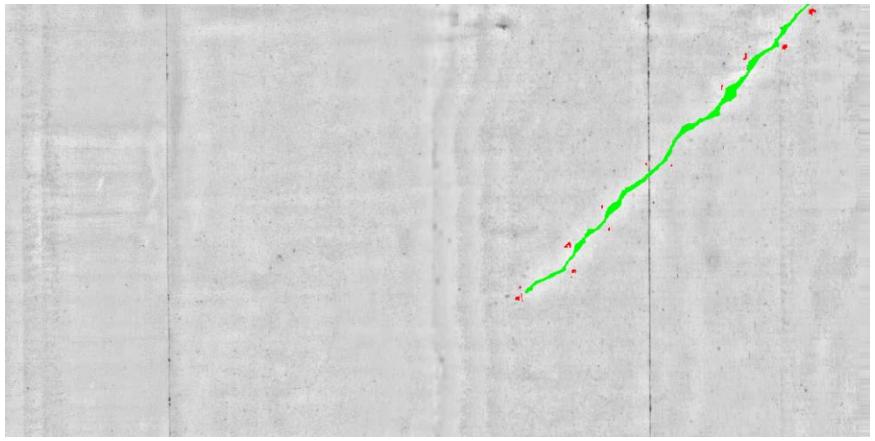
Best CrackNet



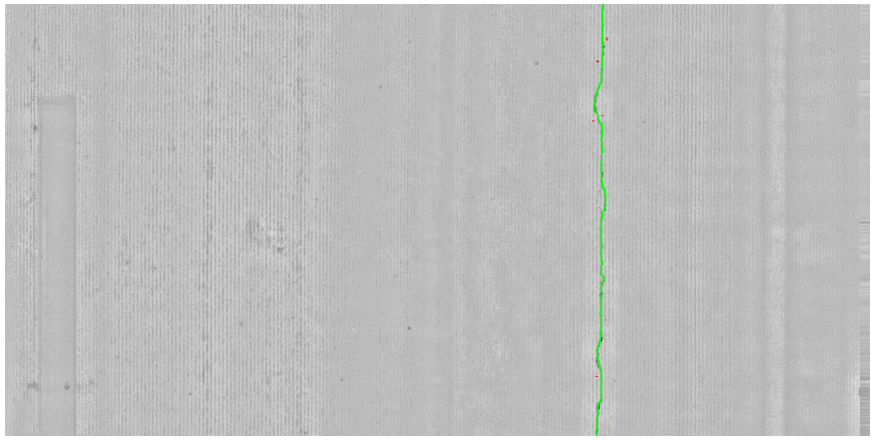
Best CrackNet + RNN

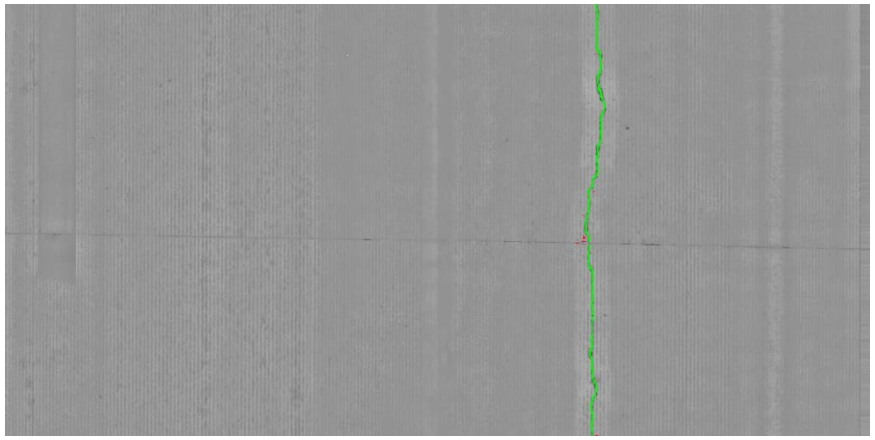
CrackNet on Rigid Surfaces





Jointed Surface





Grooved Surface

Future Work

- Exhaustive Image Library
  - 3D Pavement Data & 2D Pavement Image
  - All Variations of Pavement Distresses
  - Manually Processed Example Data
  - Artificial Example Data
- Long-term Training & Optimization
  - Network Optimization Using Diversified Data
  - Field Tests
- Self-taught Learning
  - Unsupervised Learning from Unlabeled Data;
  - Progressive Improvements in Real-time Applications
- Real-time Application
  - Massively Parallel Computing to Reduce Processing Time