Cognition-Based Intelligent Solutions for Condition and Safety Surveys

By

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- ❑US DOT University Transportation Centers
- ❑Technology Users in the US, & Other Parts of the World

Part One
Introduction and Work Status

Part Two
Work In Progress

Part One

Introduction and Work Status

Pavement Data Collection Types

- Functional: Roughness (Longitudinal, IRI)
- Surface Distresses
  - Cracking
  - Rutting
  - Faulting, and others
- Structural: Surface Deflection
  - FWD, TSD, RWD, RAPTOR, et al
- Safety: MPD, MTD, Various Friction Testing Devices per ASTM

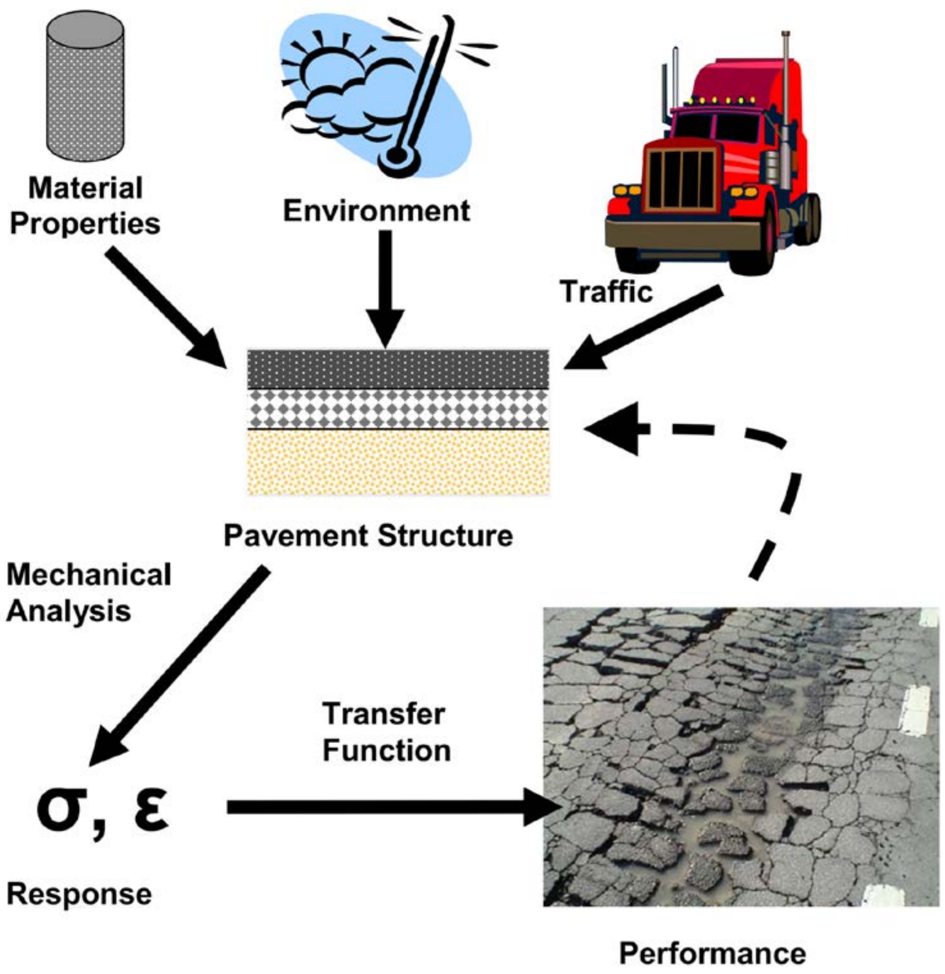
Data Collection Systems

- ❑Roughness： Relatively Mature
- ❑Surface Distresses: Not Fully Automated
  - 3D Laser Imaging: 1mm， 0.5mm， 0.1mm?
- ❑Structural Evaluation: Evolving Rapidly
  - Traditional FWD
  - High-Speed: TSD， RWD， RAPTOR， Others
- ❑Safety
  - Contact Now, and Non-Contact in the Future
  - New 0.1mm 3D Laser Imaging System?
- ❑**Ket to Solutions**
  - Software Implementations

Ultimate Challenge: Cracking

- ❑Cracking: # 1 indicator of Pavement Distresses
- ❑Need: Cracking Detections and Classifications
  - Pavement Design: Fatigue Models Rely on Accurate Cracking Data
  - Pavement Management: Distress Prediction and Rehabilitation
- ❑Status: No Usable Technology in Full Automation for Cracking Detection

Fatigue Cracking in ME Design



$$N_f = k_1 \left(\frac{1}{\varepsilon_t} \right)^{k_2}$$

- N: loading cycles to failure
- Stress & Strain (σ, ε) at Asphalt Layer Bottom

Cracking in Pavement Management

- Critical in Assessing Condition for Both Roadways and Runways for Rehabilitation and Maintenance Needs
- #1 Importance for Surface Condition Survey

Accurate Cracking Data Thru Automation

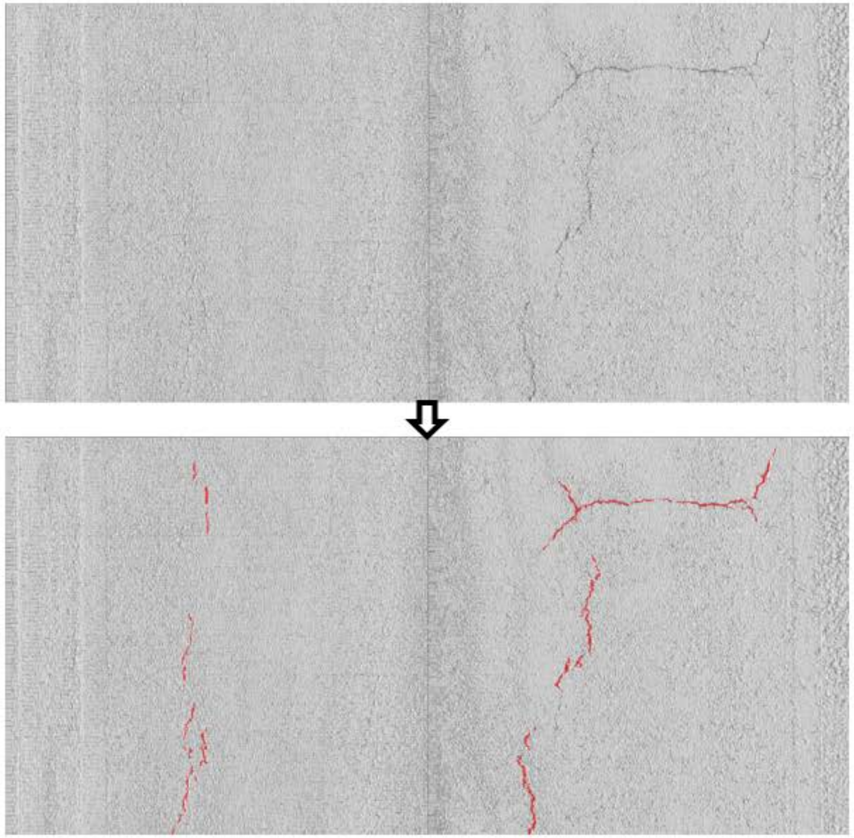
- ❑Extreme Difficulty due to Complexity
  - ➢Pavement Surface: A Highly Complicated Environment with Extensive Uncertainties
  - ➢Distress Identification: Challenging Even for Well-Trained Human Operators
  - ➢Diverse Pavement Surface Texture
  - ➢Presence of Various Pavement Distresses
  - ➢Diversified protocols of cracking definitions

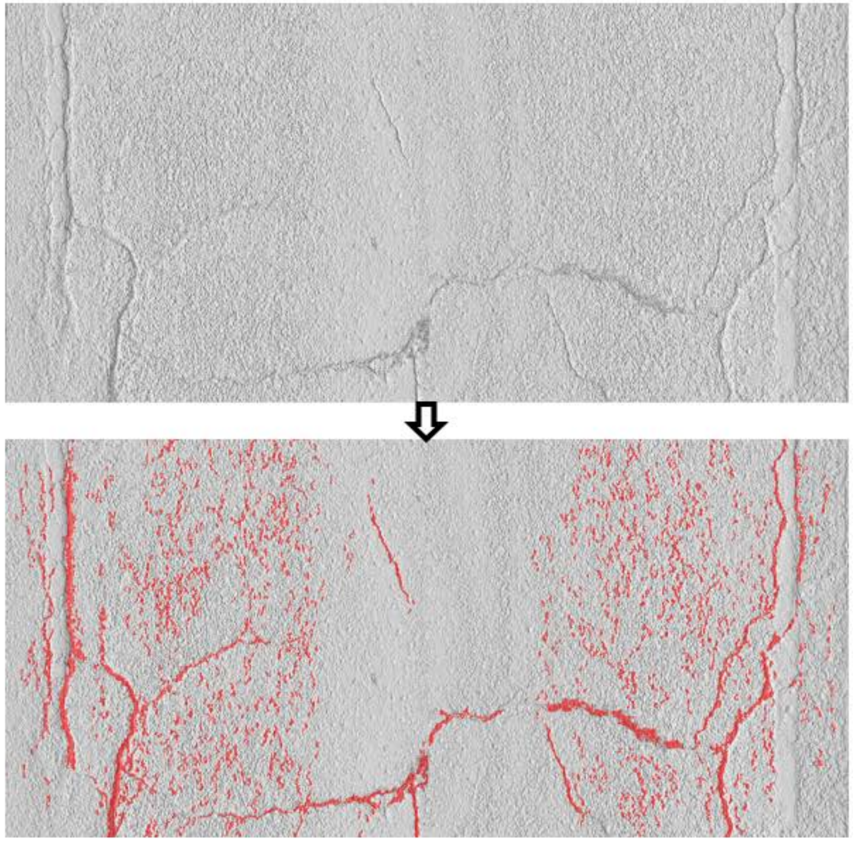
Limitations, Traditional Algorithms

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

Common Failures, Traditional Method

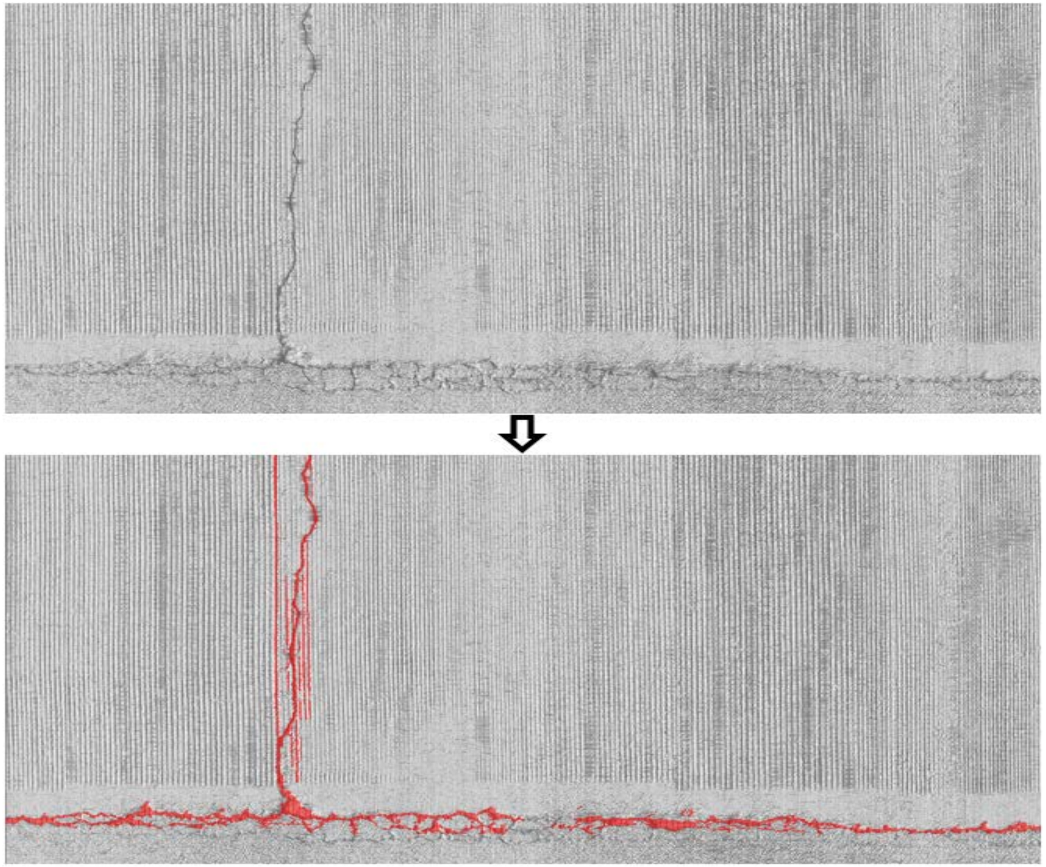
- Inconsistent Accuracies for Pavement with Various Texture


Smooth Pavement Surface


Highly Textured Pavement Surface

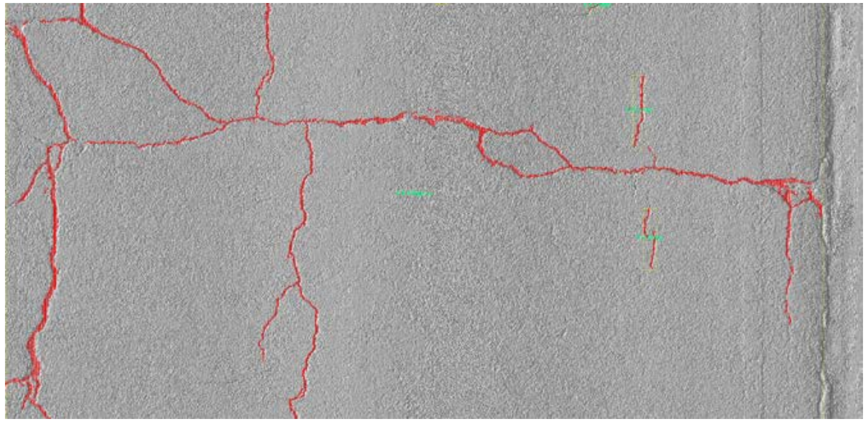
Common Failures, Traditional Method

- ❑Interference from Other Patterns

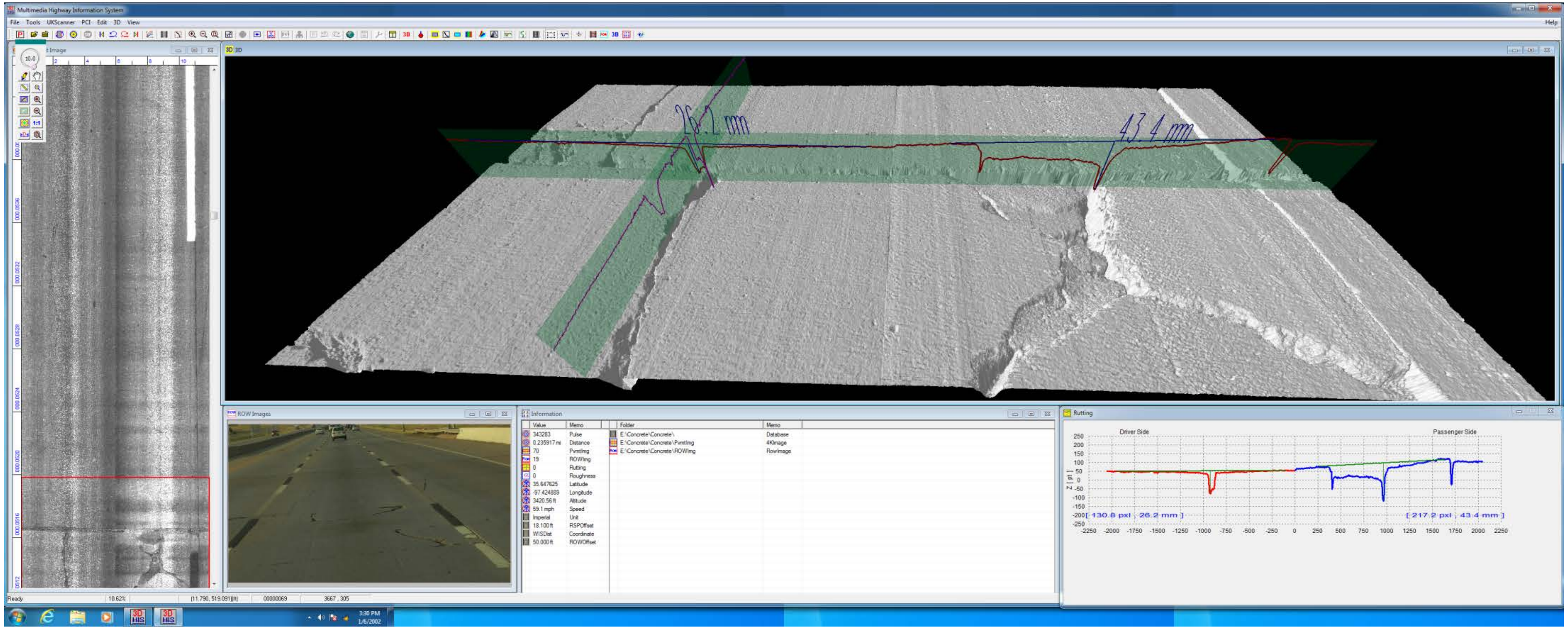


Ultimate Objectives

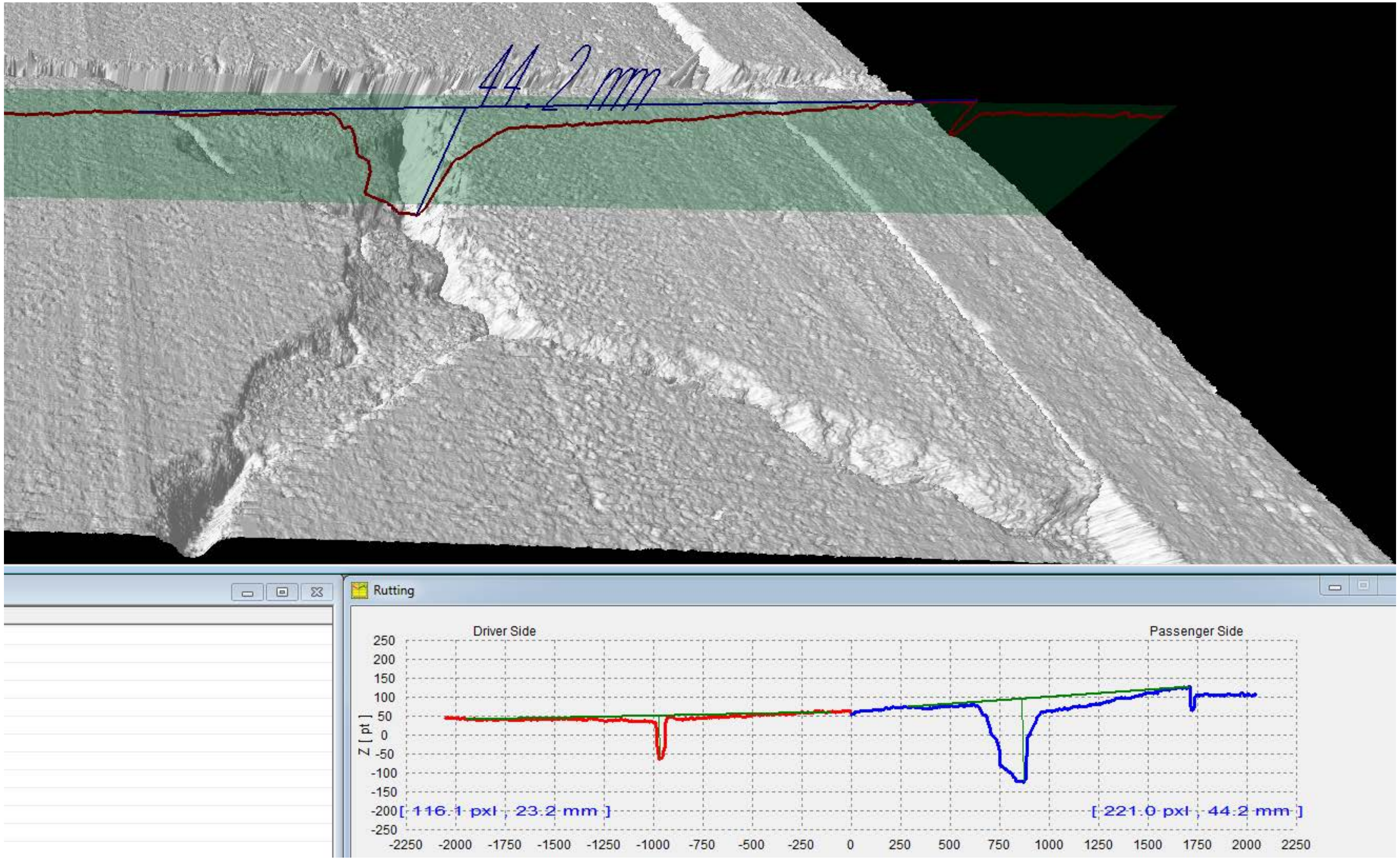
- ❑ Automated Crack Detection
  - ➢ Find the Actual Location of Distresses with Pixel-Perfect Accuracy
- ❑ Automated Crack Classification
  - ➢ Label Distress Types



3D Data at 60MPH (100KM/h)

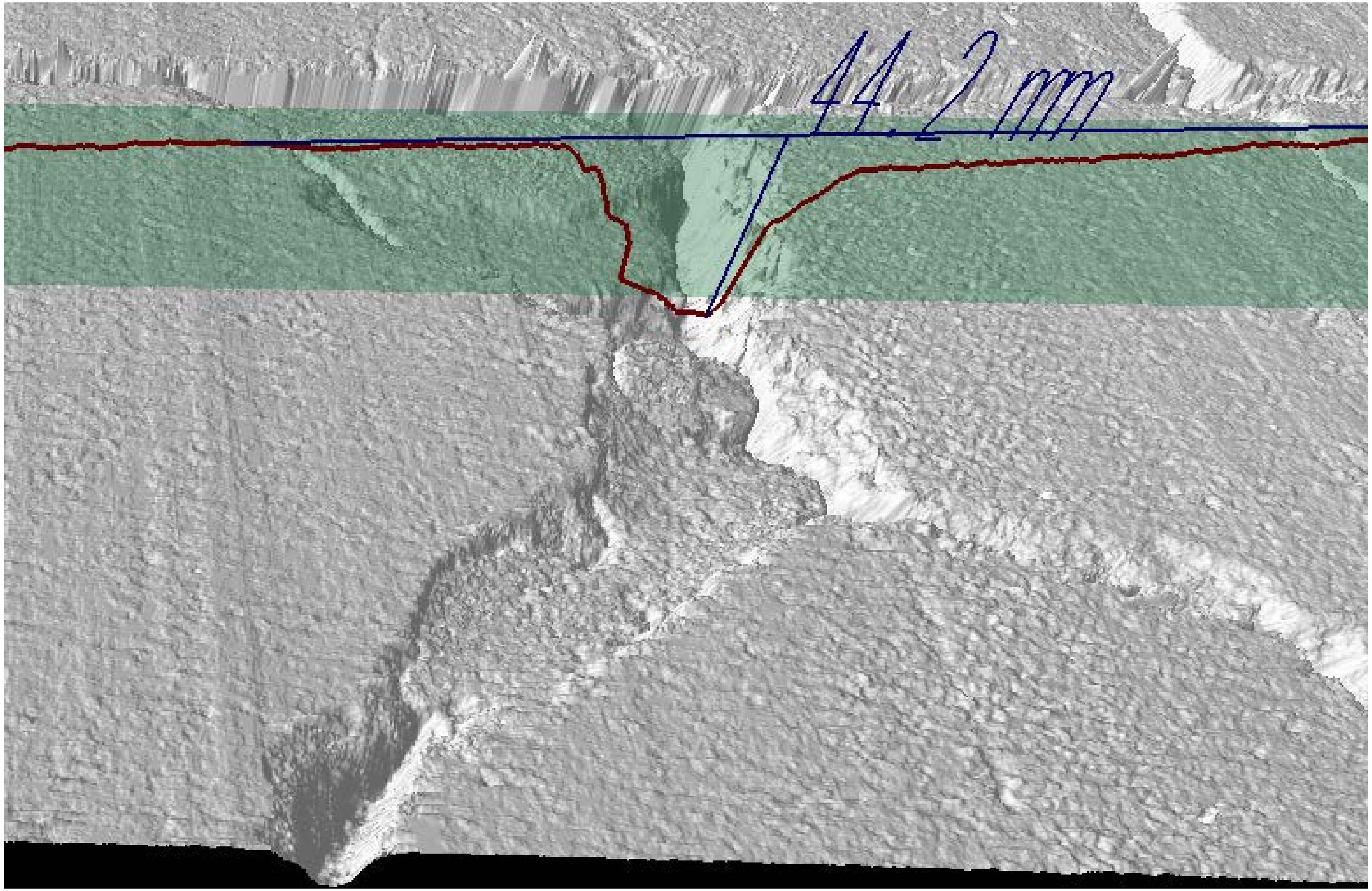


3D Data at 60MPH (100KM/h)



RPUG Road Profile Users' Group

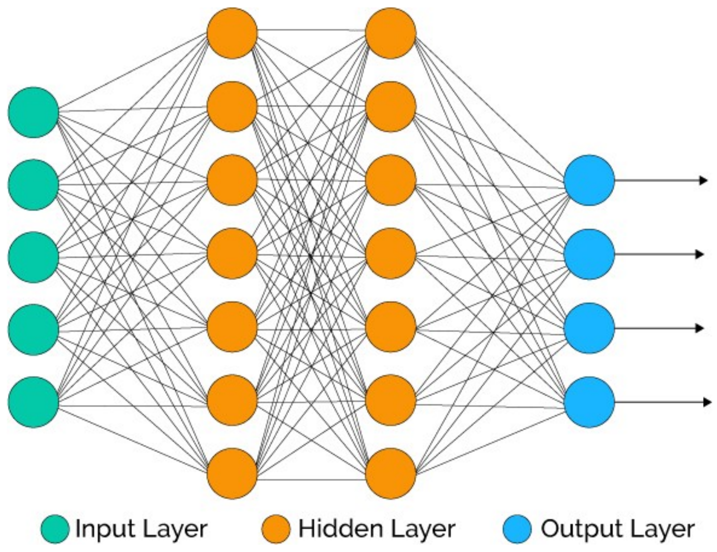
3D Data at 60MPH (100KM/h)



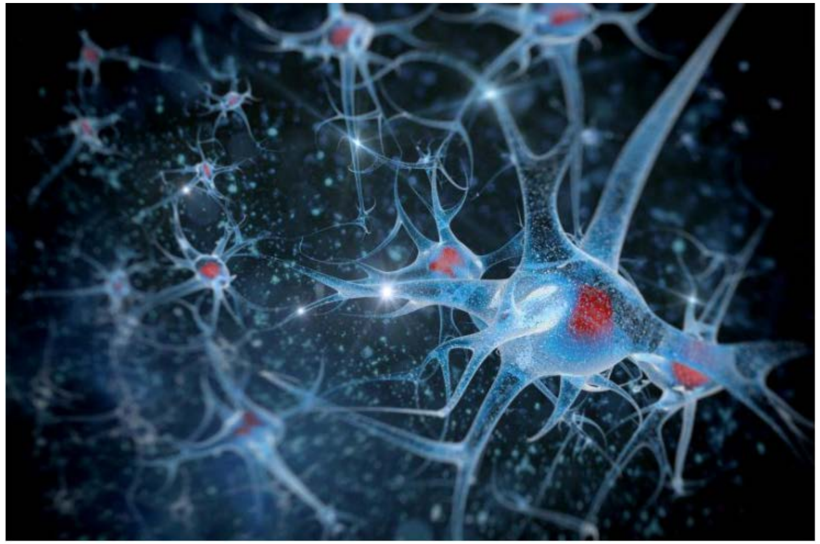
Goal of Automation:

Location and Geometries of Cracking Information

Traditional Artificial Neuron Net



# of Neurons<10^4

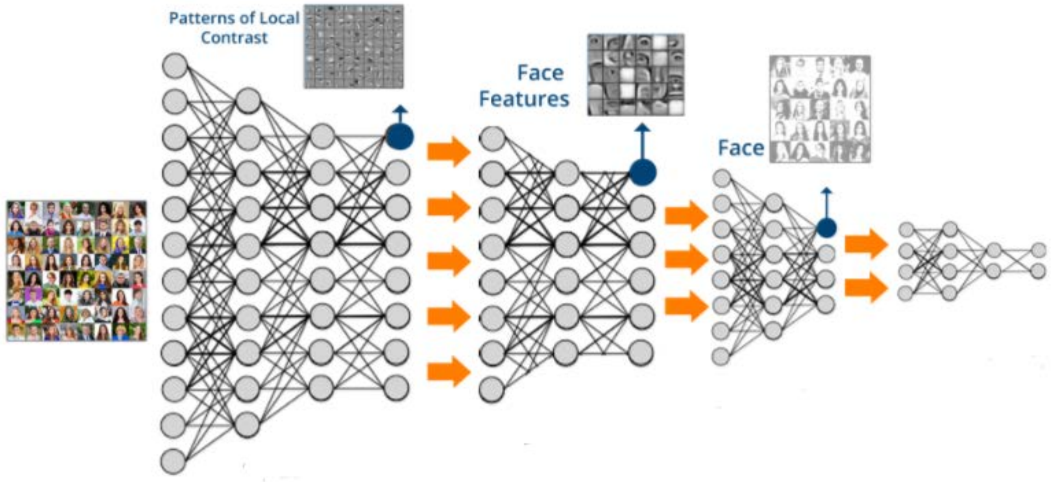


# of Neurons=10^{11} (Human Brain)

- ❑Shallow Abstraction
  - ➢Limited Number of Layers & Neurons
  - ➢Cannot Fully Reflect the Complexity of Problems
- ❑Limited Amount of Data

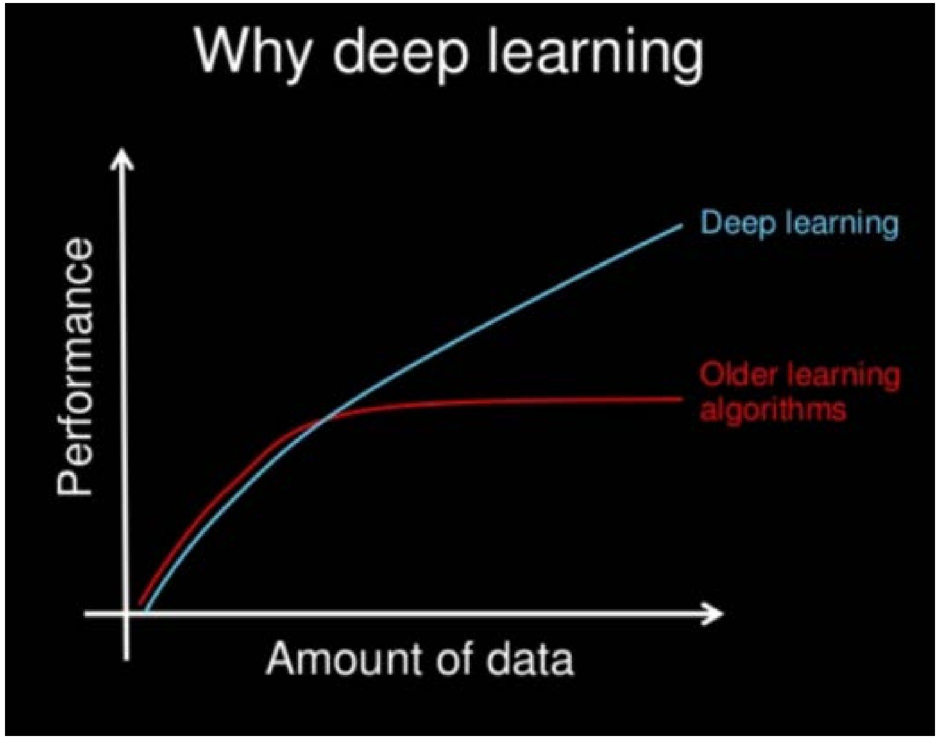
Deep Learning

- ❑Deep Abstraction
  - # of Layers: 10^1-10^3
  - Exploit Understanding on Complex Problems
- ❑Complex Connections Among Neurons
  - # of Connections Per Neuron: 10^2-10^4
- ❑Enhanced Reliability
  - Feed with Exhaustive Variations of Example Data

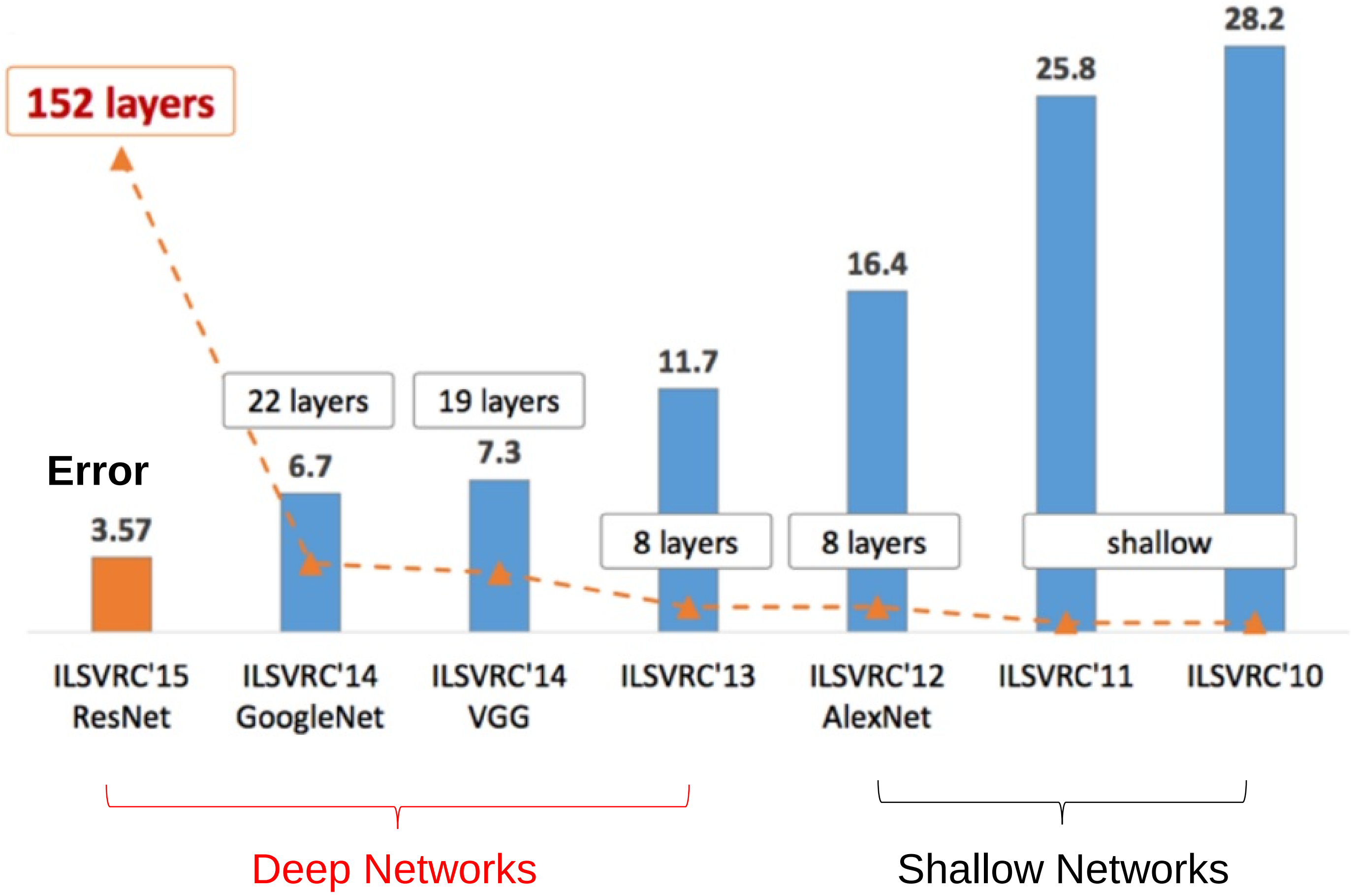


Why Deep Learning?

- ❑Strong Learning Ability and Versatility
- ❑Enhanced Reliability through Continuing Learning
- ❑Knowledge Accumulation: as to Human Learning

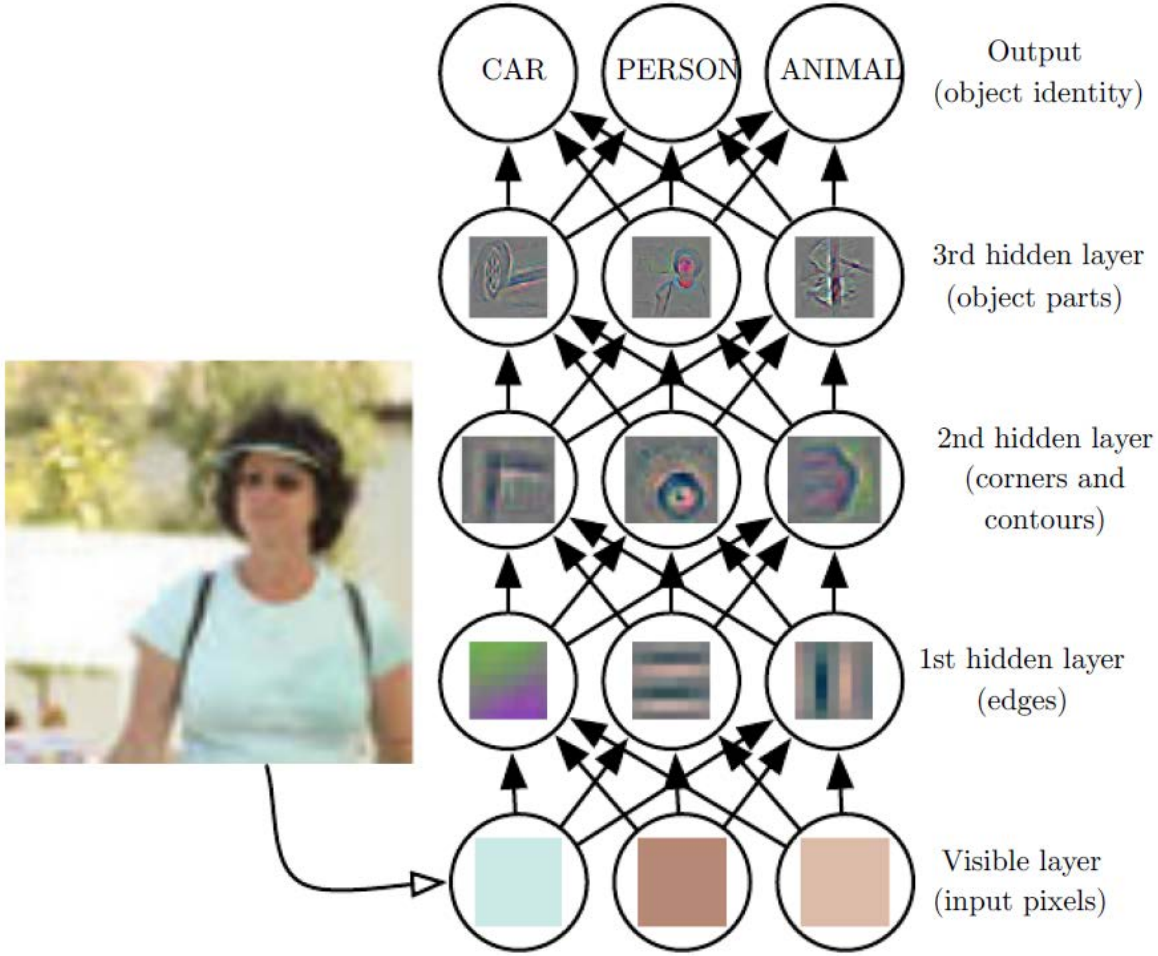


Shallow vs. Deep Networks



ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

Image Model of CNN: Learning Cognition



(Goodfellow et al., ***Deep Learning***, 2016)

DL Design for Pavement Cracking

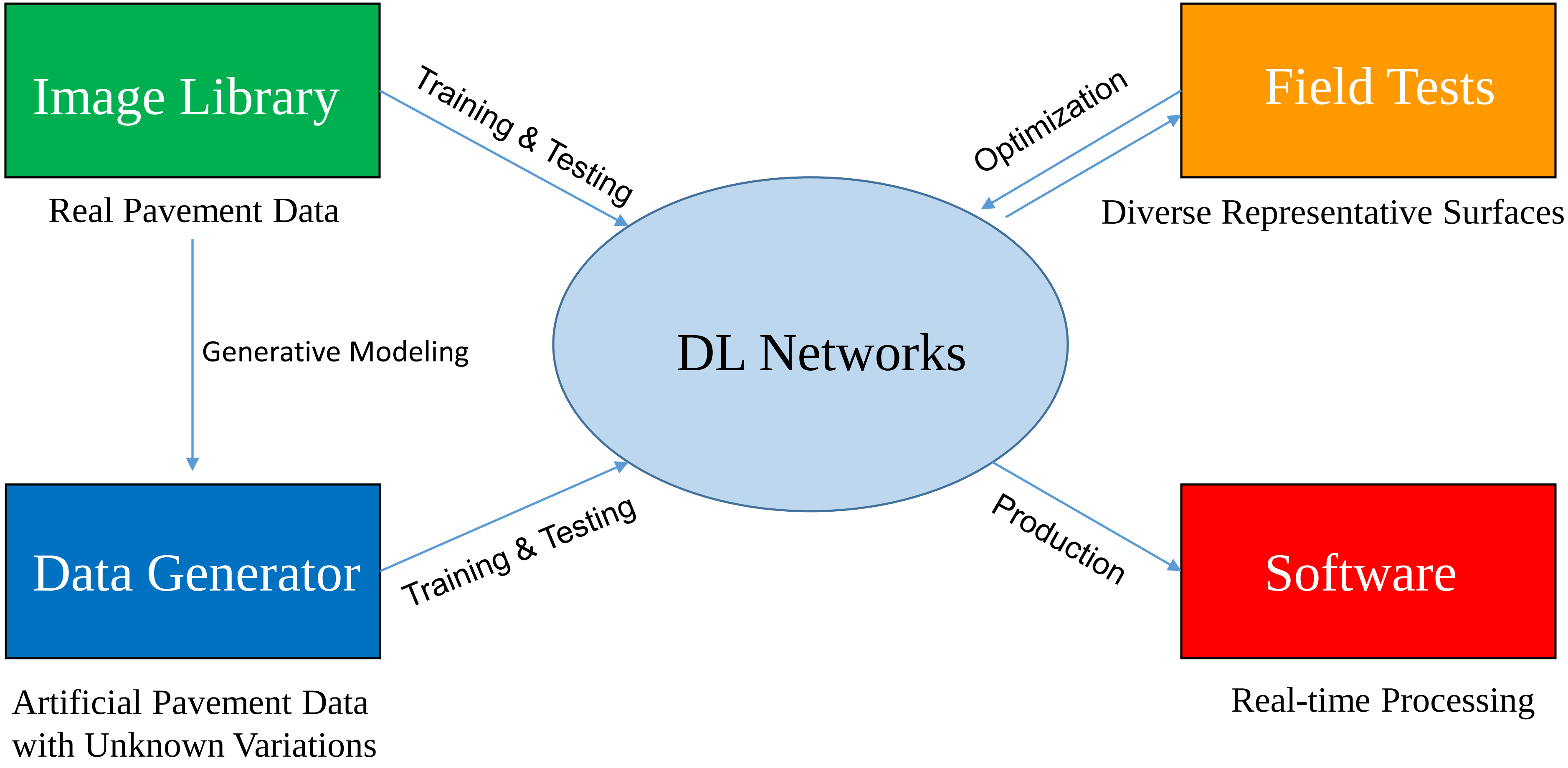
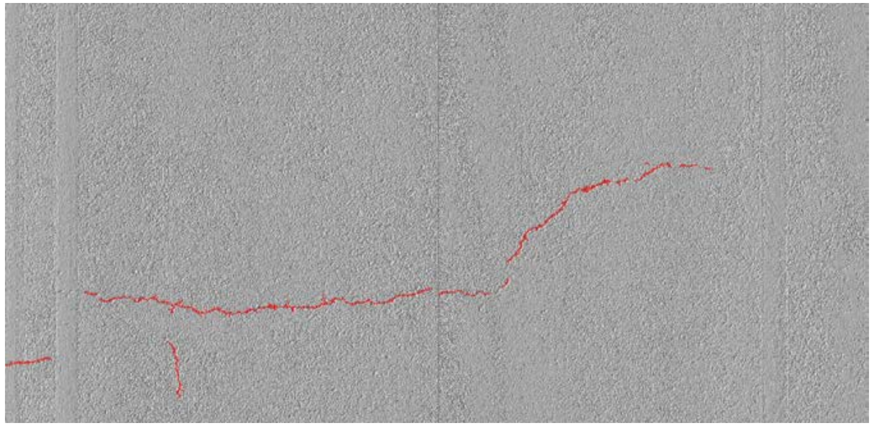
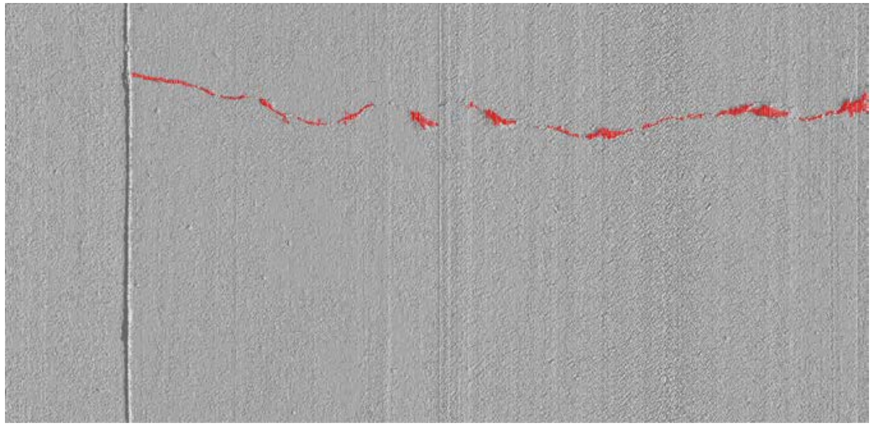
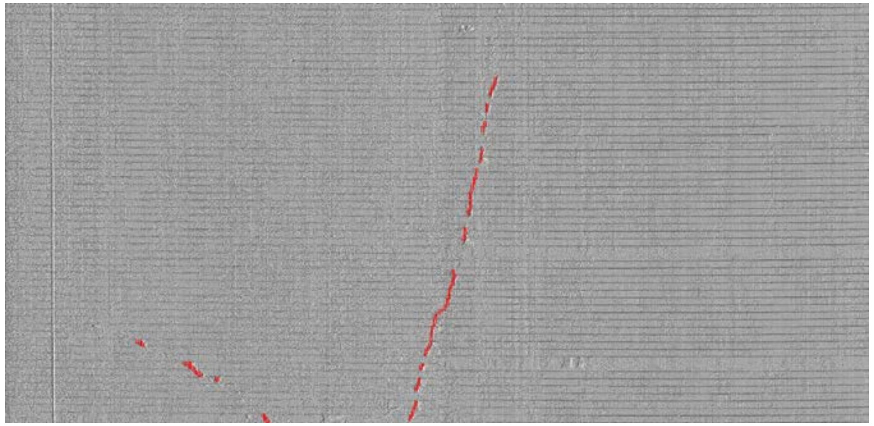
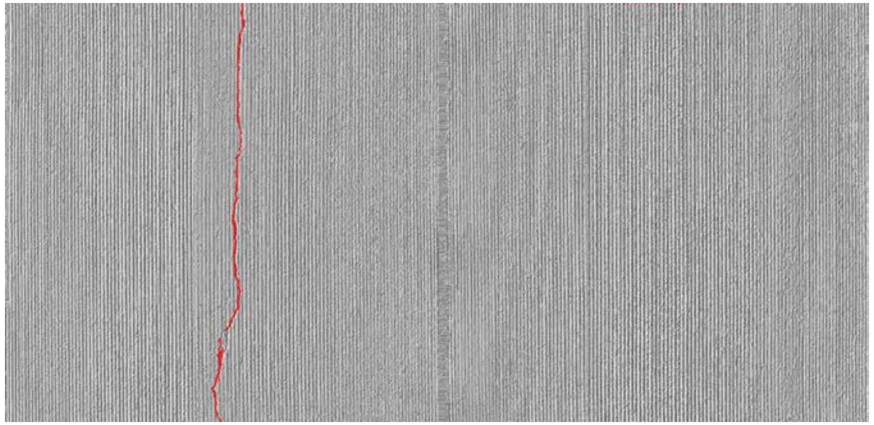


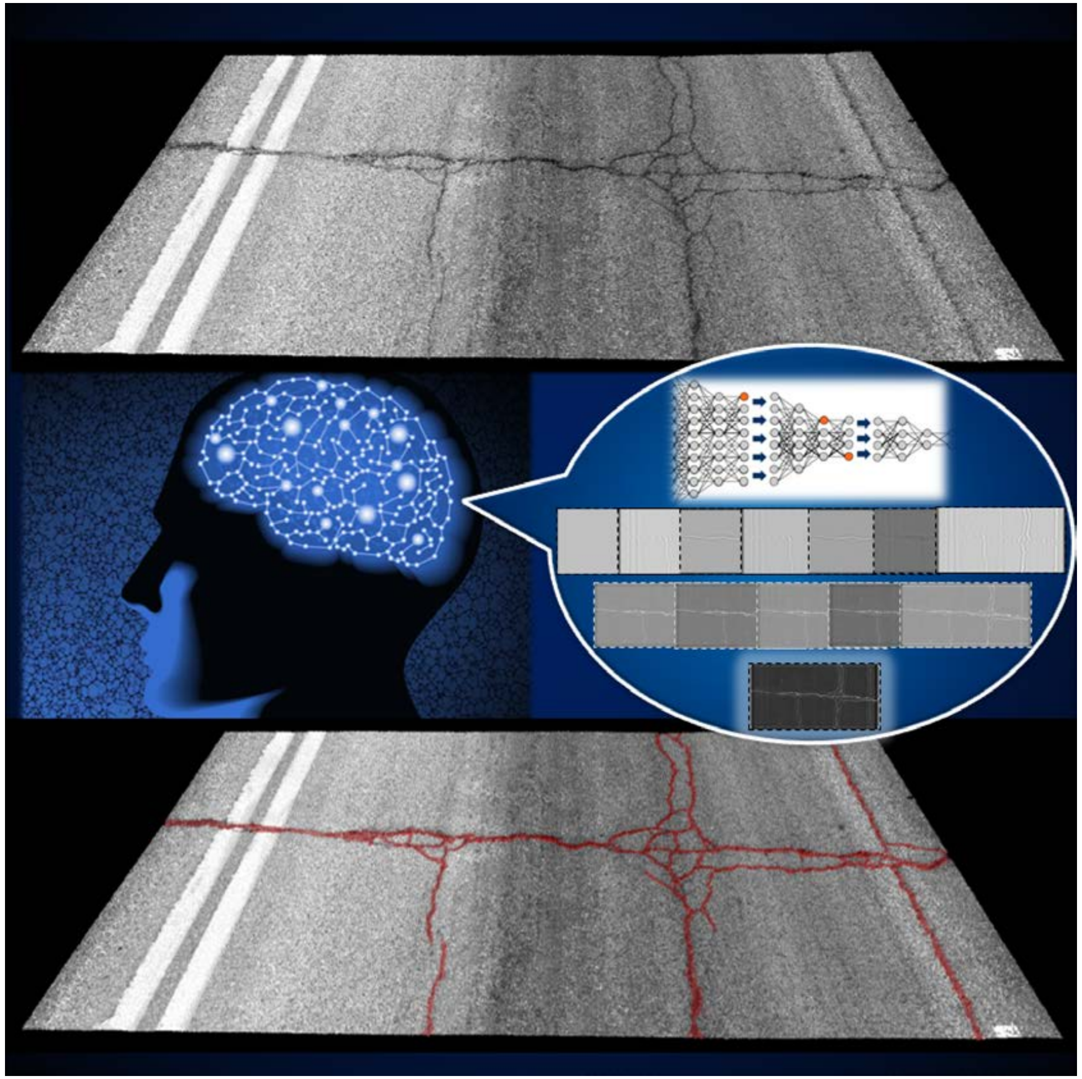
Image Library: Basis of Learning

- Data Type
  - 3D Pavement Data & 2D Pavement 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 or Verified
- Diversity
  - All Typical Variations of Pavement Distresses

Typical Labeled Examples, Image Library

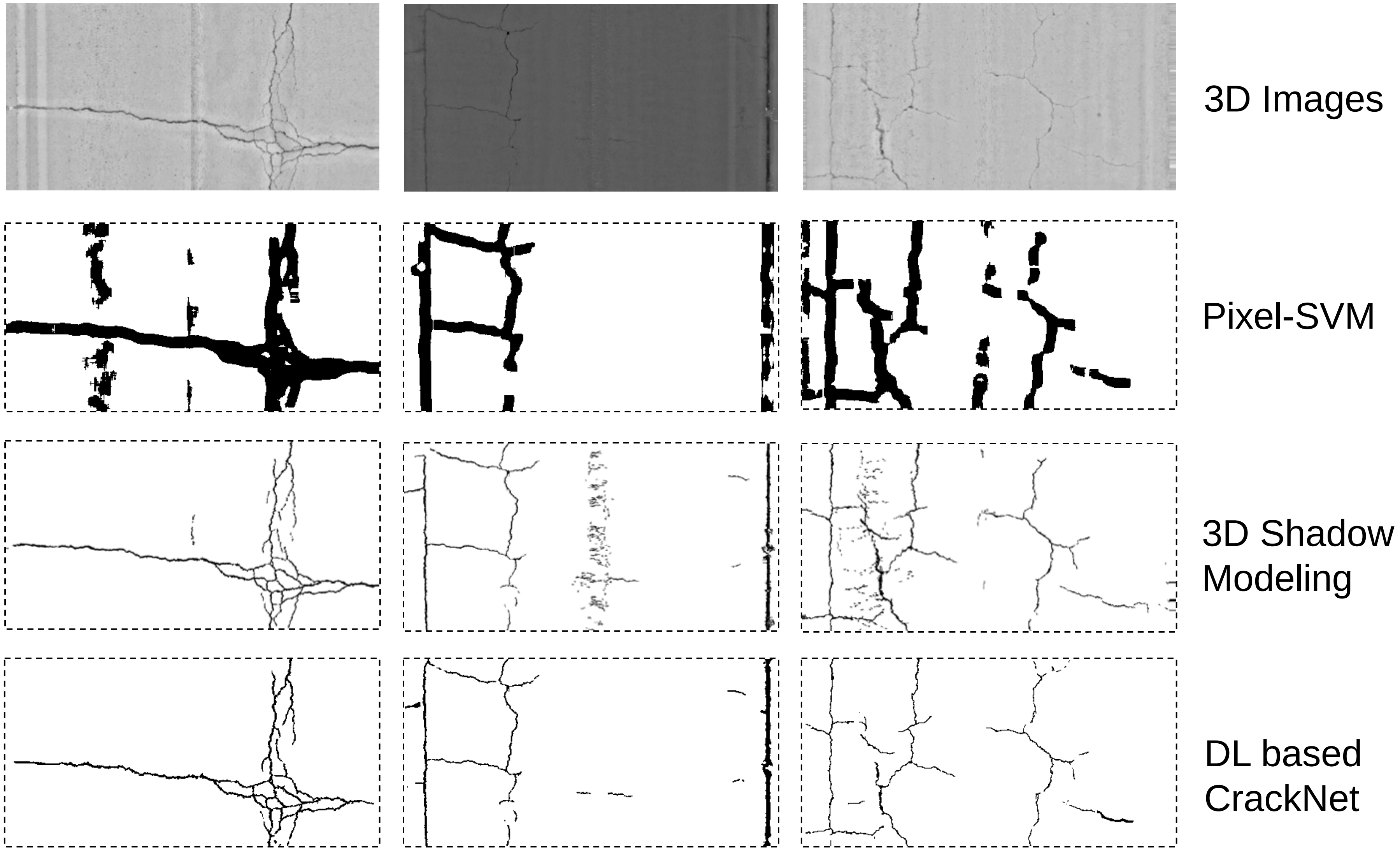





CrackNet

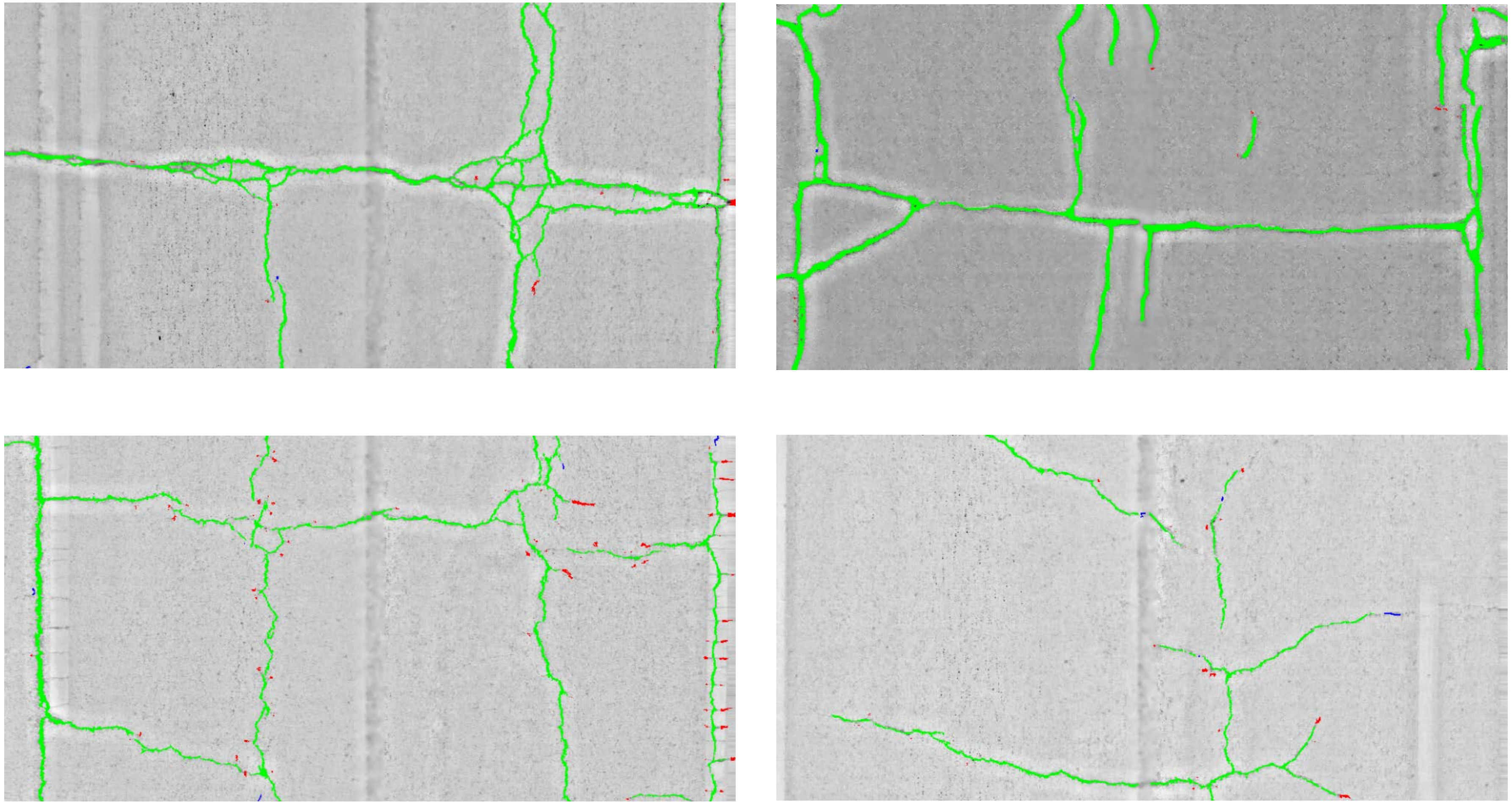


- ❑Pixel-Level Accuracy
- ❑Concrete & Asphalt
- ❑Parallel Computing
- ❑Consistent Efficiency

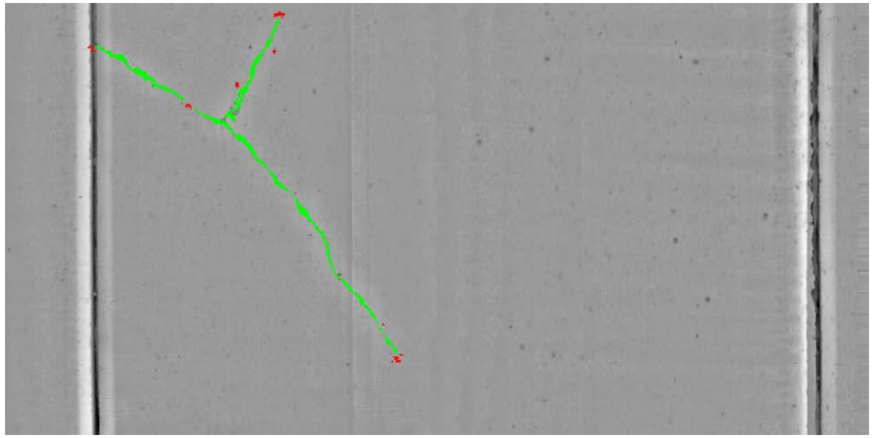
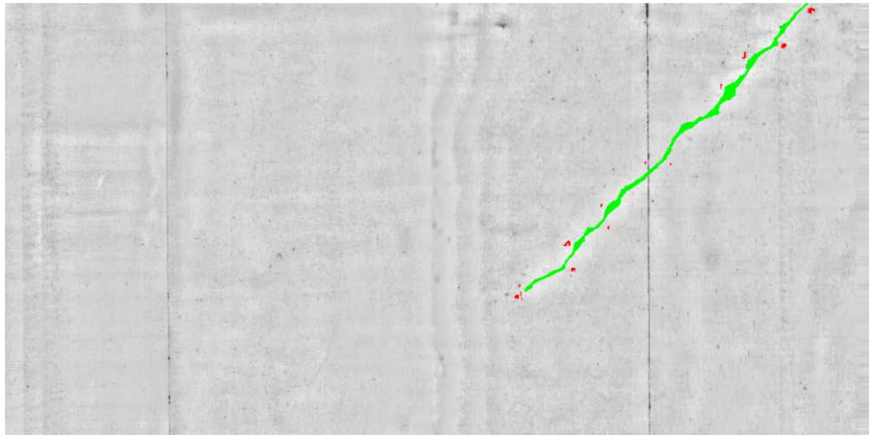
Traditional Algorithms vs. CrackNet



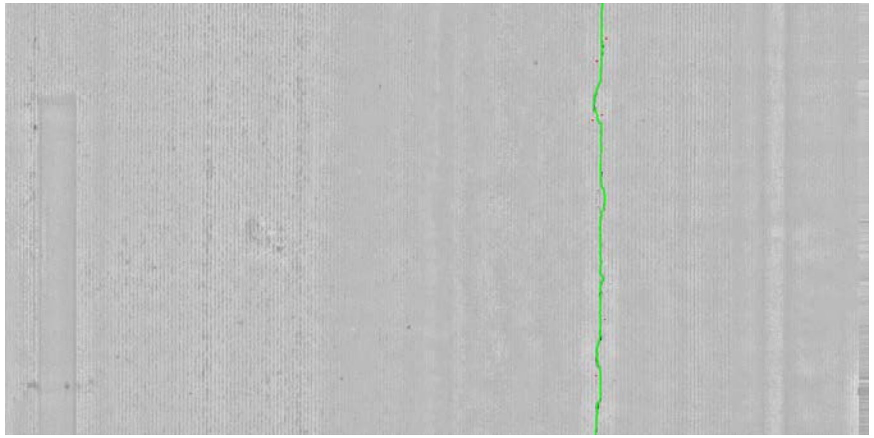
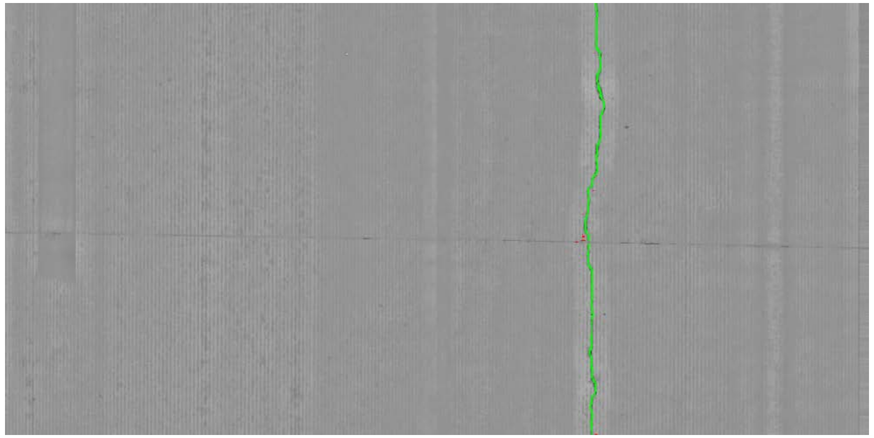
CrackNet for Flexible Surfaces



CrackNet for Rigid Surfaces

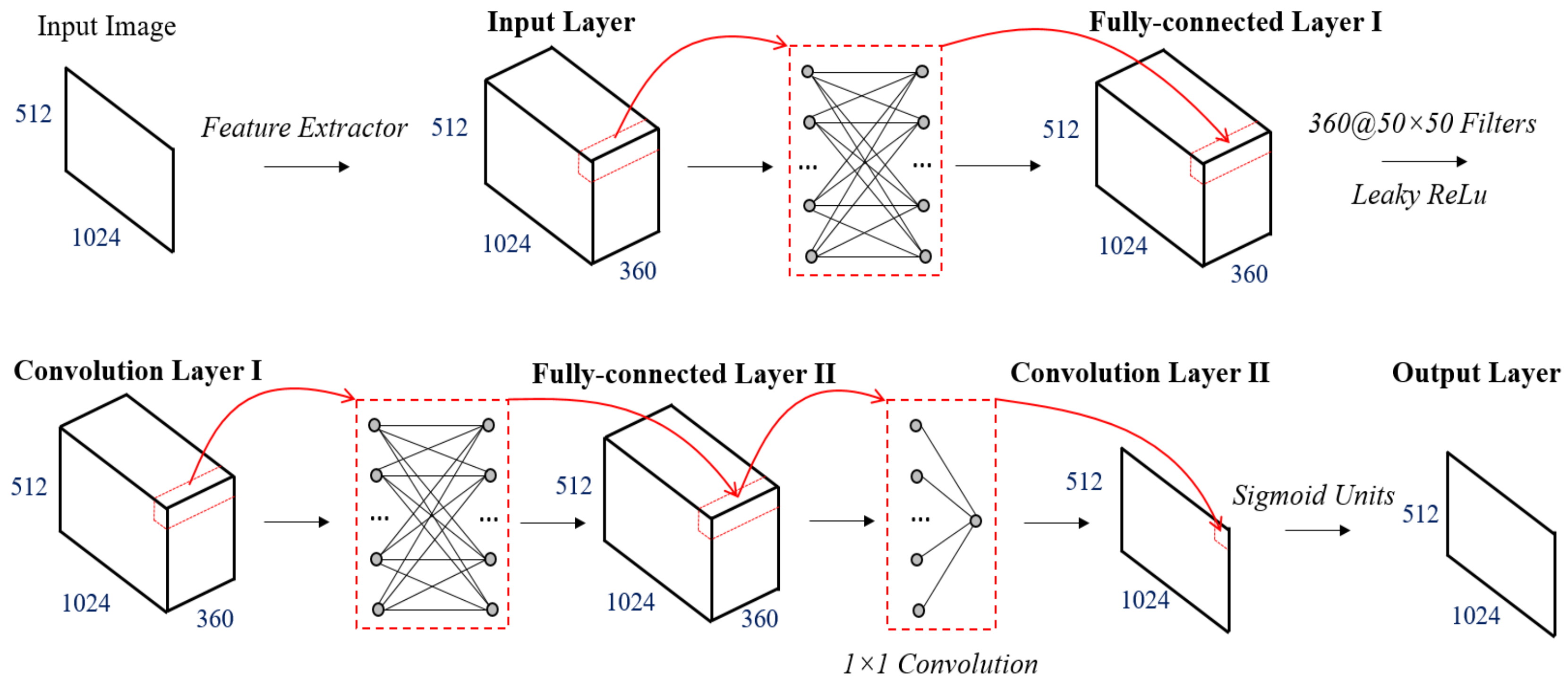



Jointed Surface

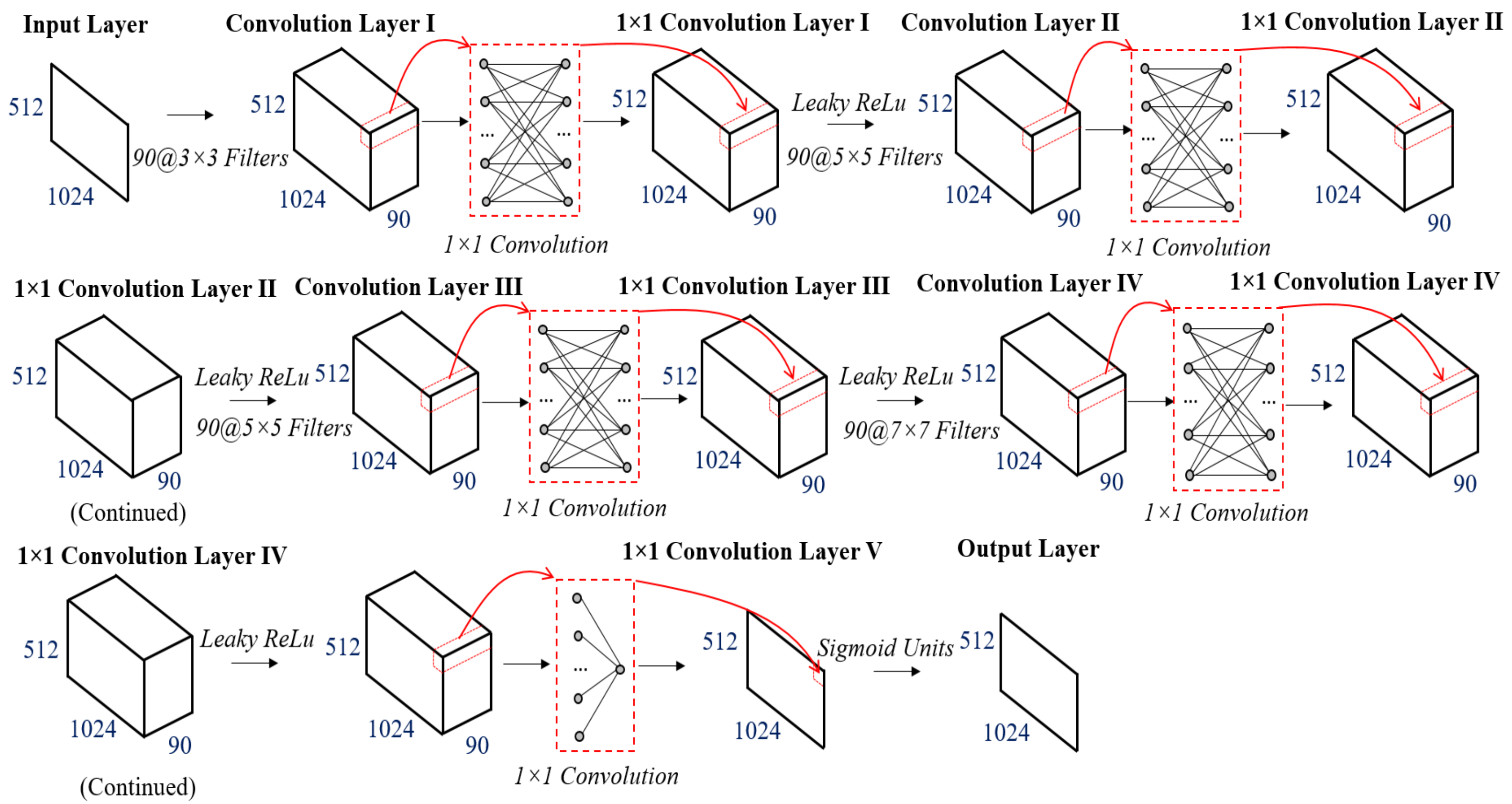
Grooved Surface

CrackNet I



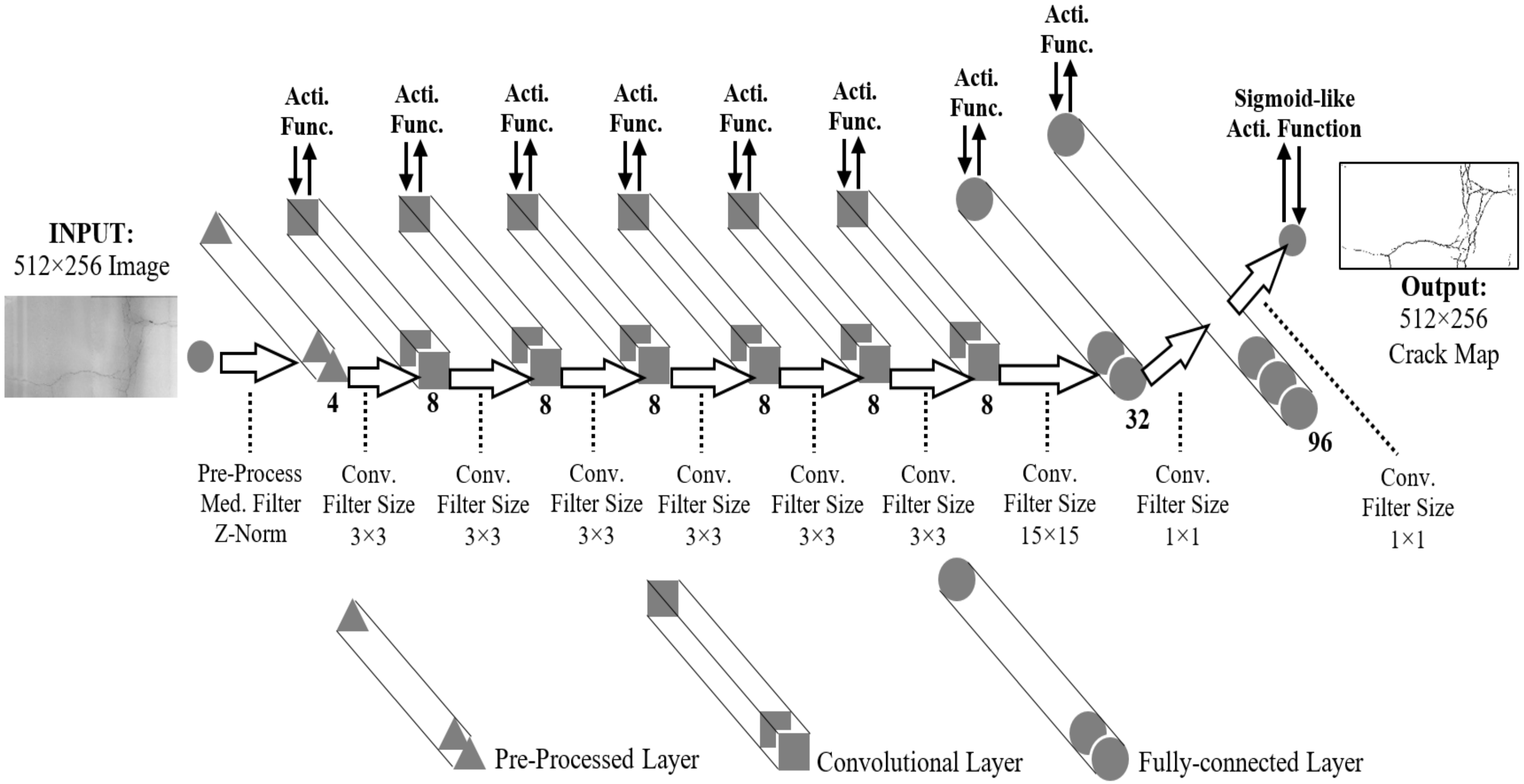
- ❑Convolutional Neural Network
- ❑7 Layers
- ❑1,159,561 Parameters

CrackNet II



- ❑Convolutional Neural Network
- ❑10 Layers
- ❑42,571 Parameters

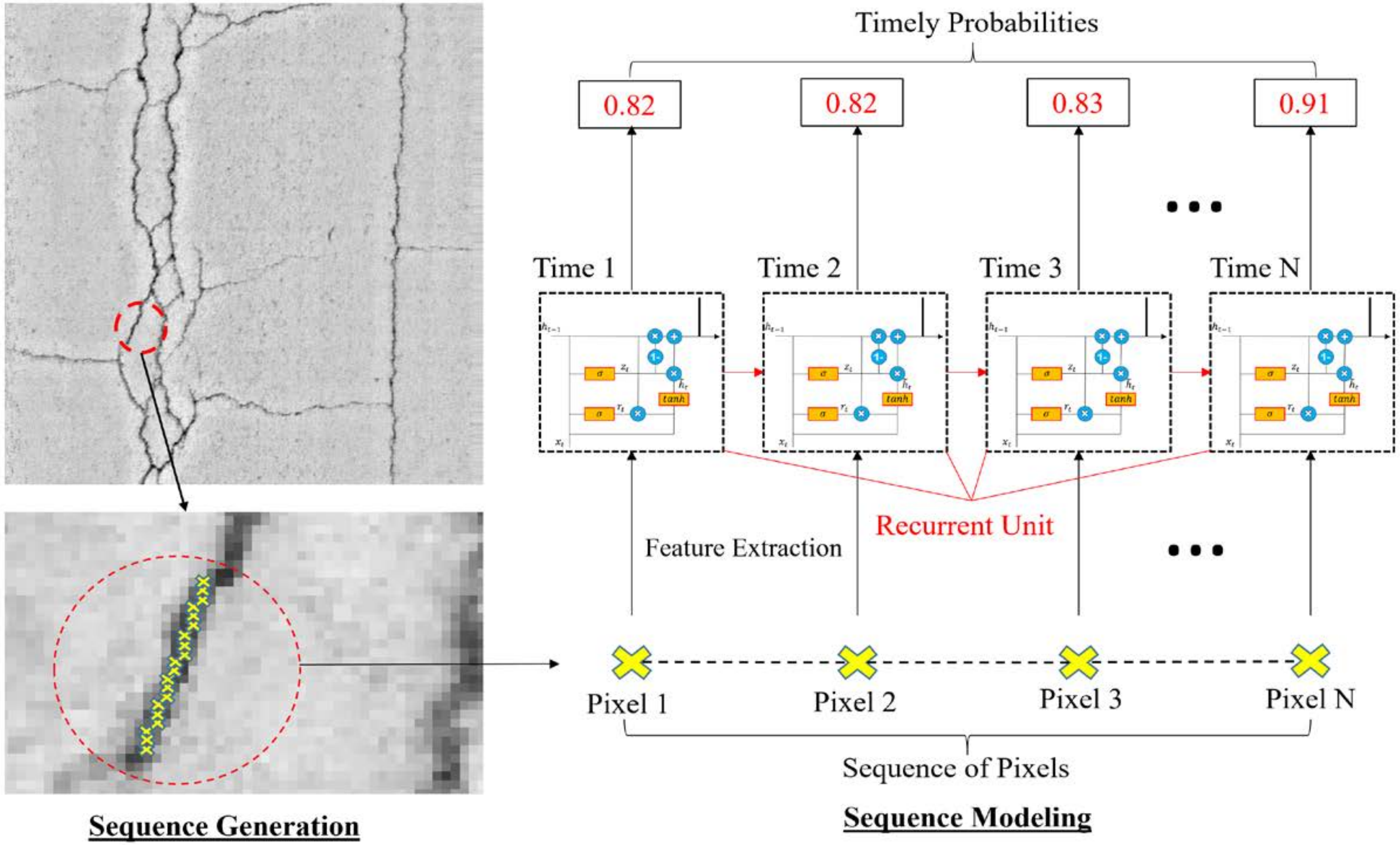
CrackNet-V



- ❑Based on VGG
- ❑9 Layers
- ❑64,113 Parameters

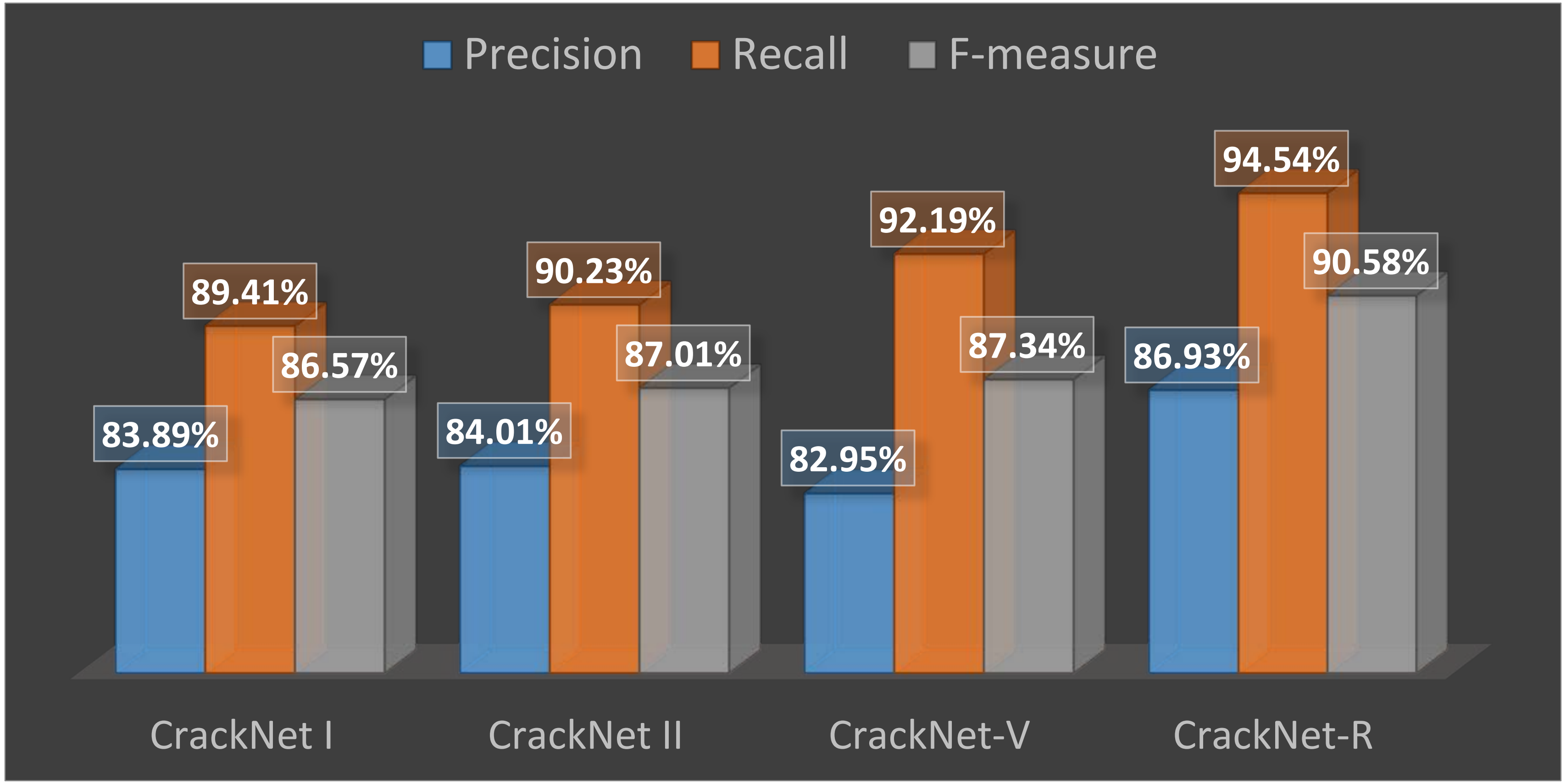
RPUG Road Profile Users' Group

CrackNet-R



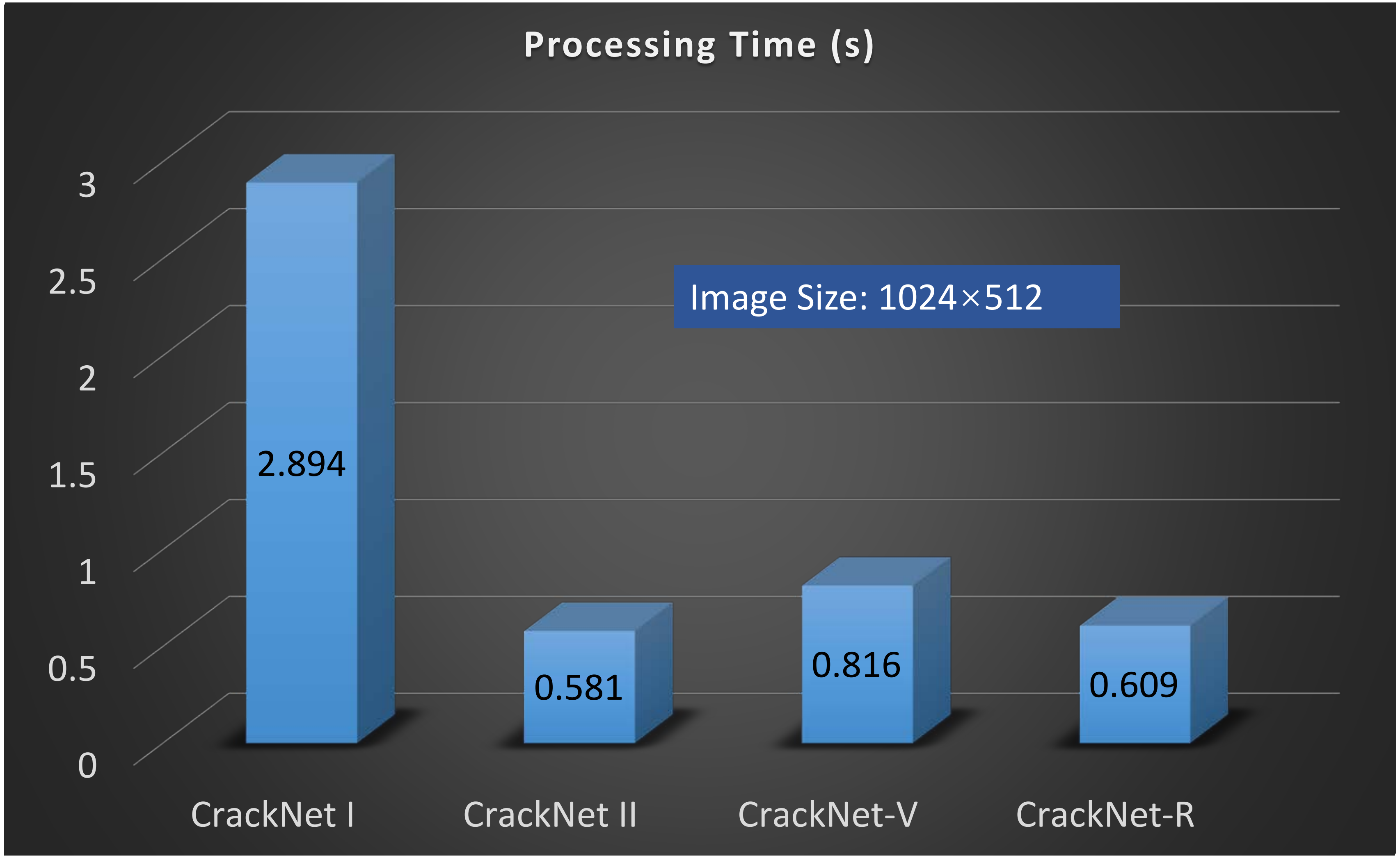
- ❑Recurrent Neural Network
- ❑Recurrent Unit: Gated Recurrent Unit (GRU)

Performance Comparison

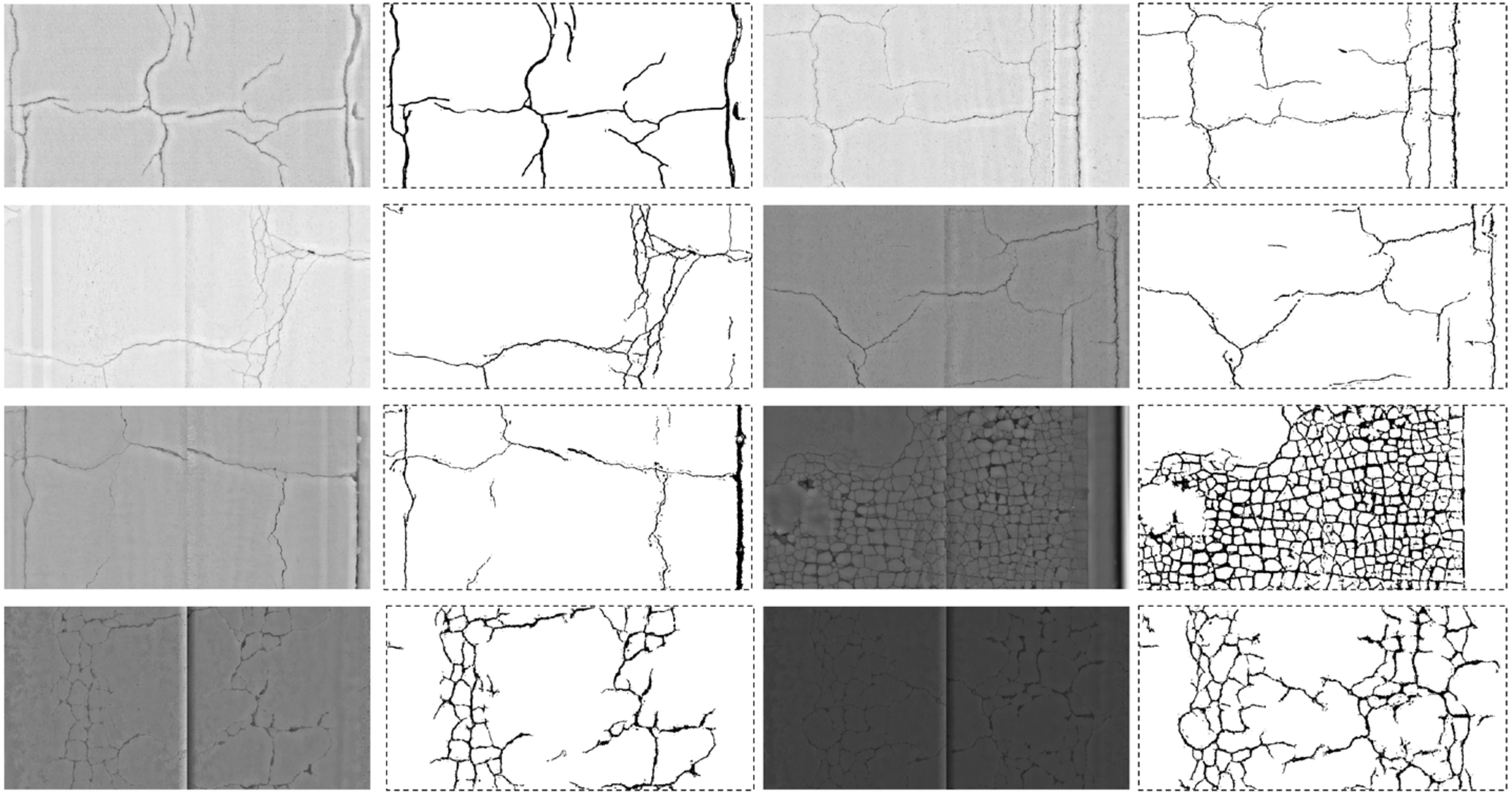


Precision=True Positive/(True Positive + False Positive): False Positive
Recall=True Positive/(True Positive + False Negative): False Negative
F-measure=2×Precision×Recall/(Precision + Recall): Composite

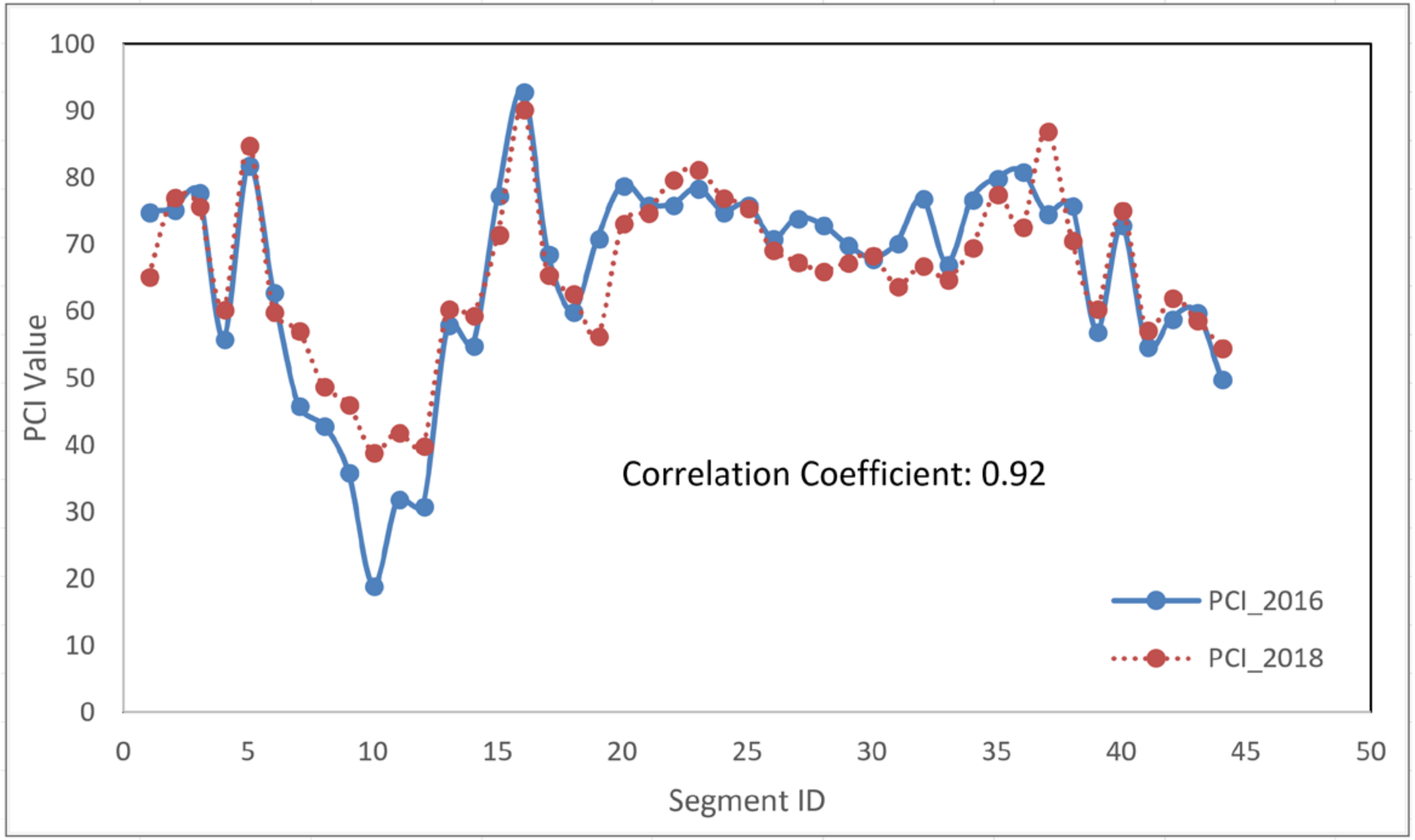
Speed Comparison



Typical Performance of CrackNet-R



An Example of CrackNet Effectiveness



- ❑PCI Data from A Large County in the US
- ❑Manual PCI (2106) & Fully Automated PCI (CrackNet in 2018)

Part Two

Work In Progress:

1. Generative Adversarial Networks (GANs)

2. Spatial Pyramid Pooling

3. New High-Performance Sensors from 1mm to 0.1mm

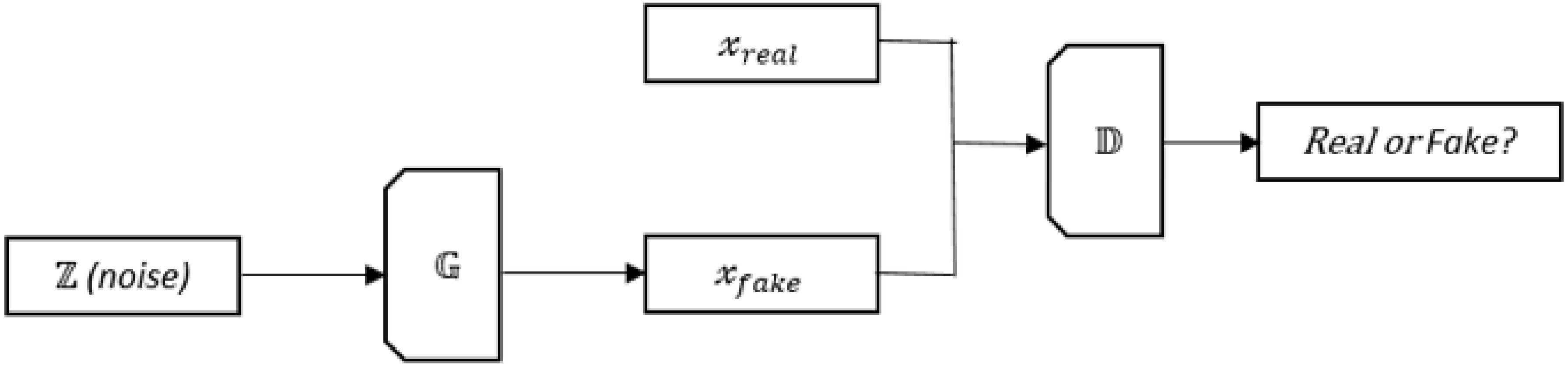
Generative Adversarial Networks (GANs)

- A class of artificial intelligence algorithms used in unsupervised machine learning
- Implemented by a system of two neural networks contesting with each other in a zero-sum game framework
- Can generate photographs superficially authentic to human observers

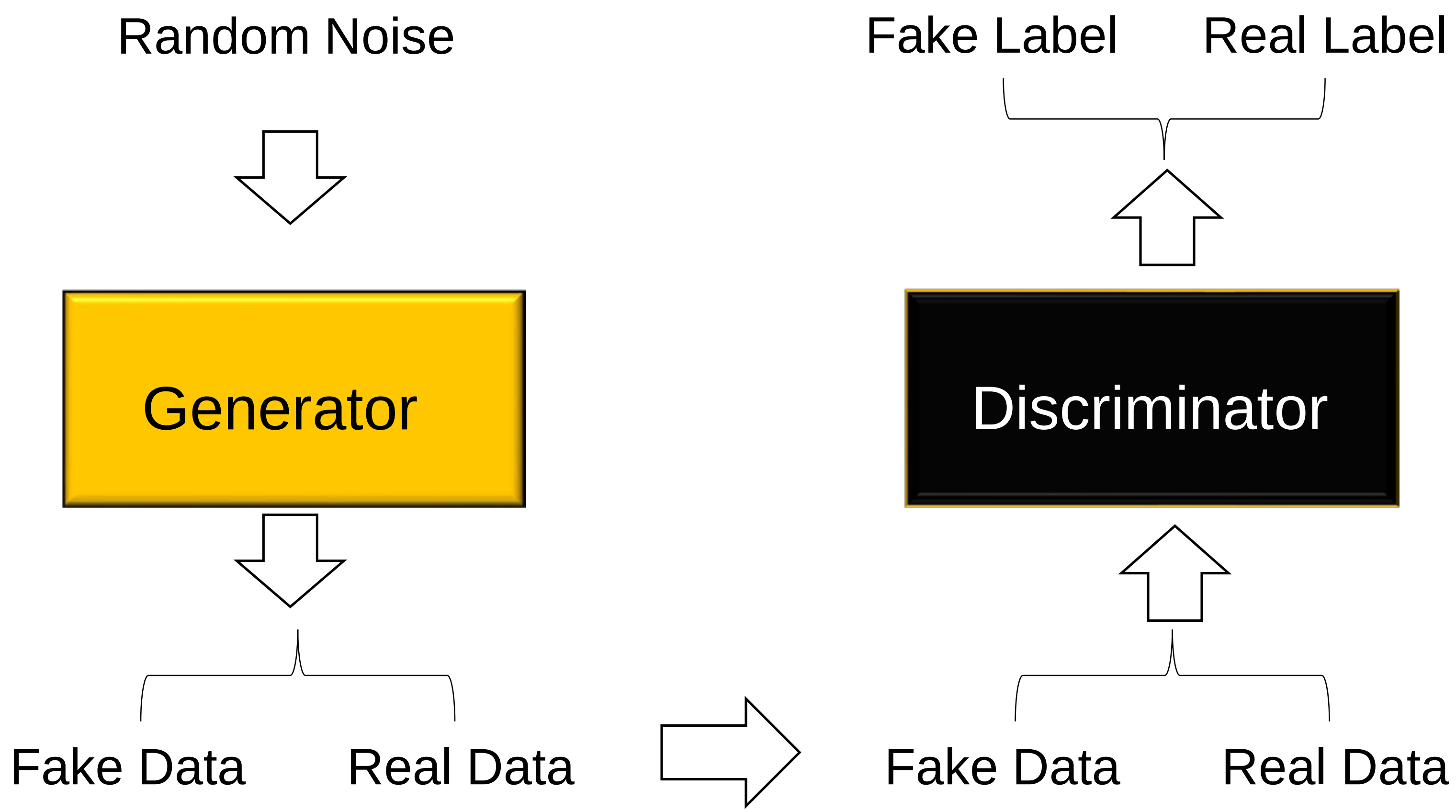
Goodfellow, et al (2014). "Generative Adversarial Networks"

Basic GANs Structure

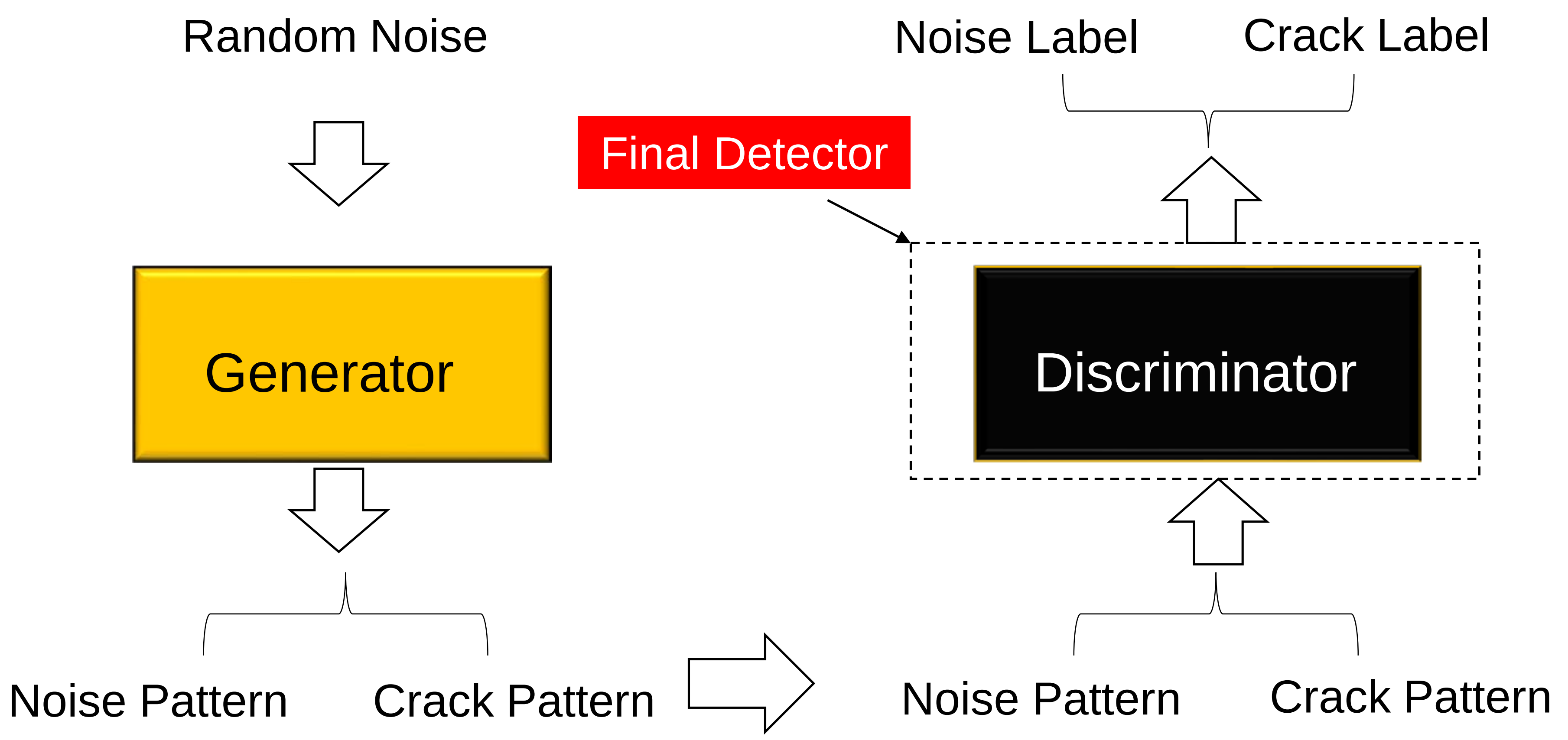
- Proposed by Ian J. Goodfellow et al. 2014
- Generator network (G)
- Discriminator network (D)
- G and D are competing against each other in a minmax game



Principles of GANs



GANs for Crack Detection



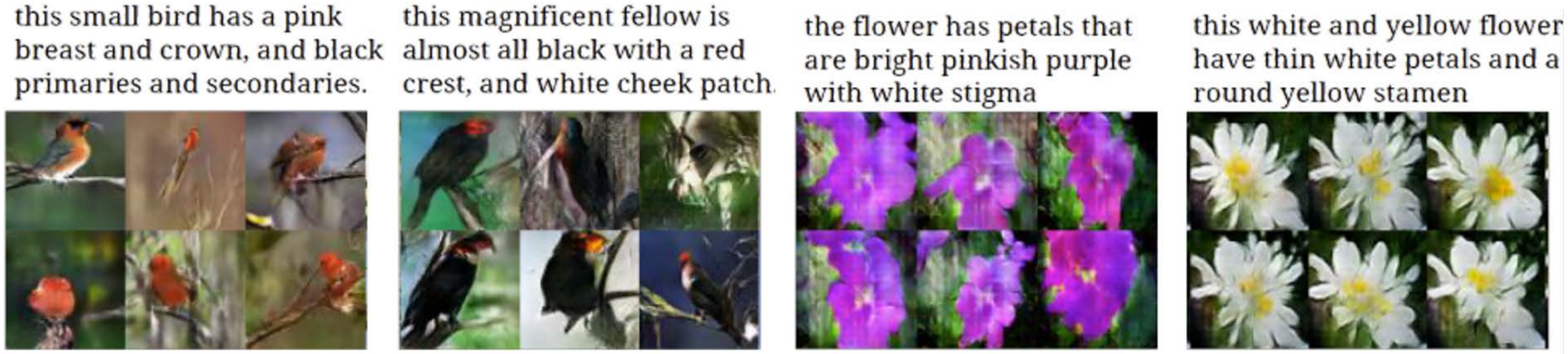
Basic GANs Structure for Cracking

- GAN Based Crack Generation
- GAN Based Noise Discriminator
- GAN Based Image Quality Enhancer

GANs Applications

- Generate images

- Translate images



Problem Statement I

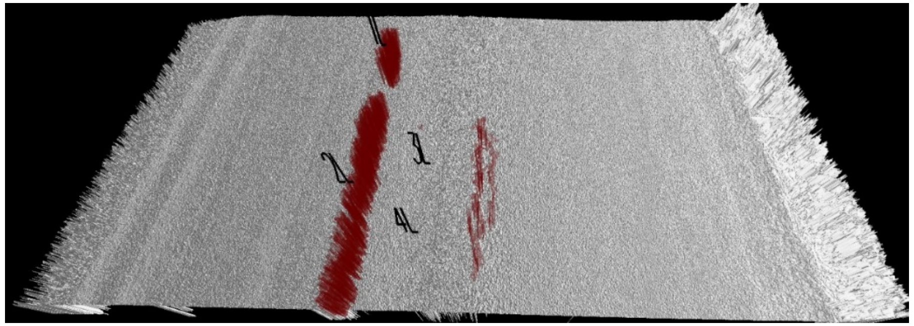
- Generate Deep Learning Training Data
  - Time consuming
  - Error prone

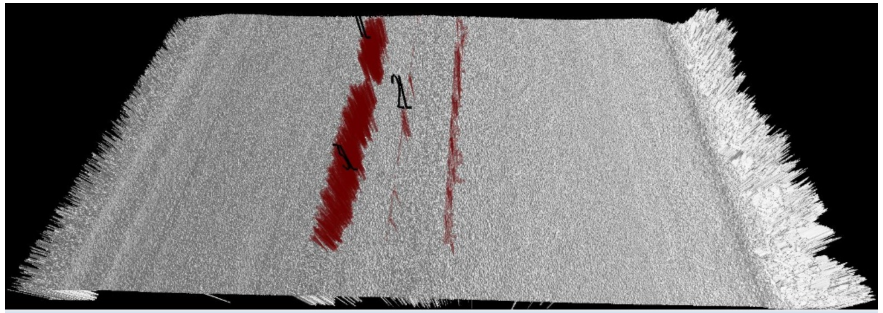
Problem Statement II

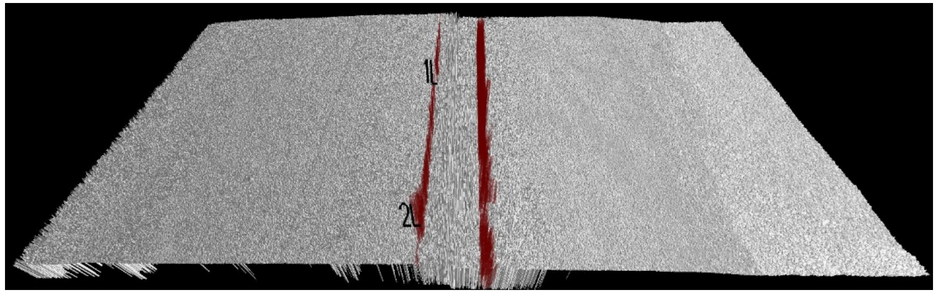
- Noise Causes False-Positive Results

Problem Statement II

- False-Positive Results Caused by Weak Laser brightness

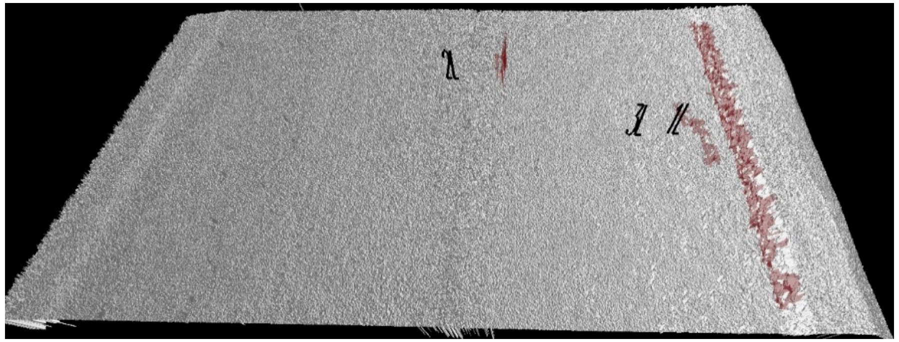


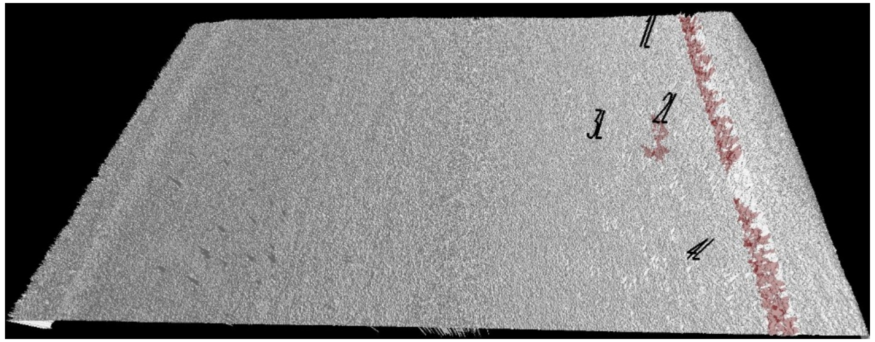


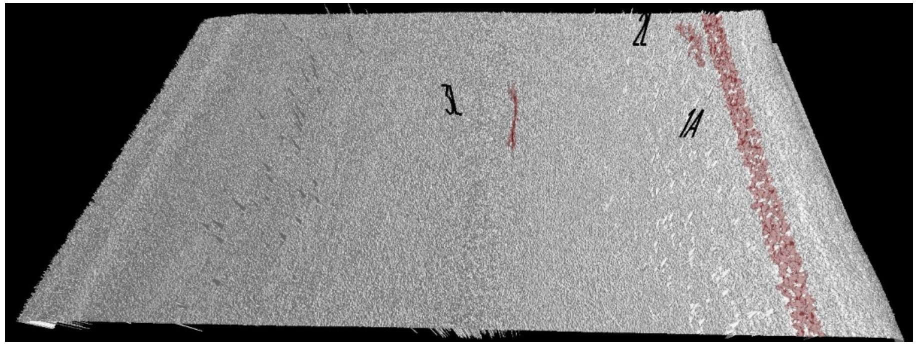


Problem Statement II

- False-Positive Results Caused by Strong laser brightness

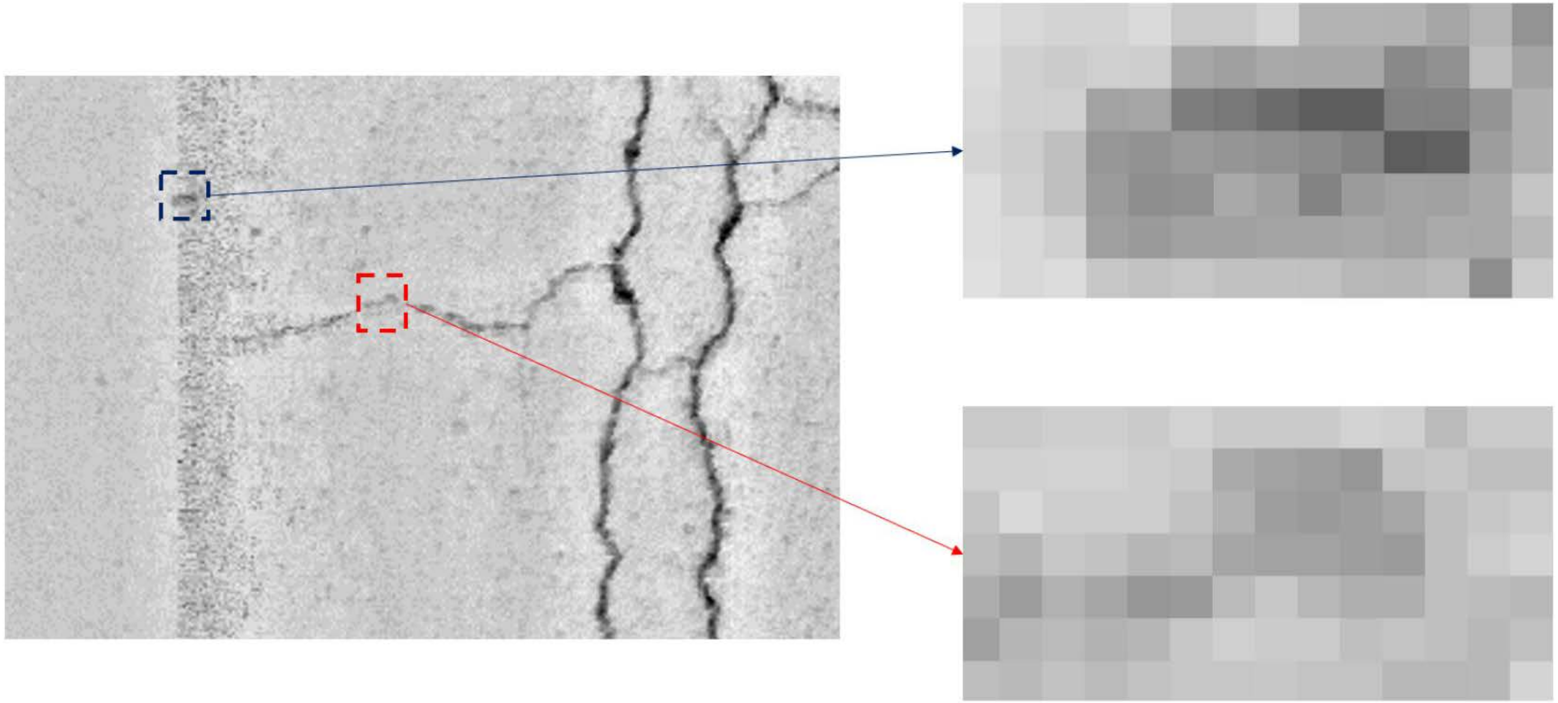






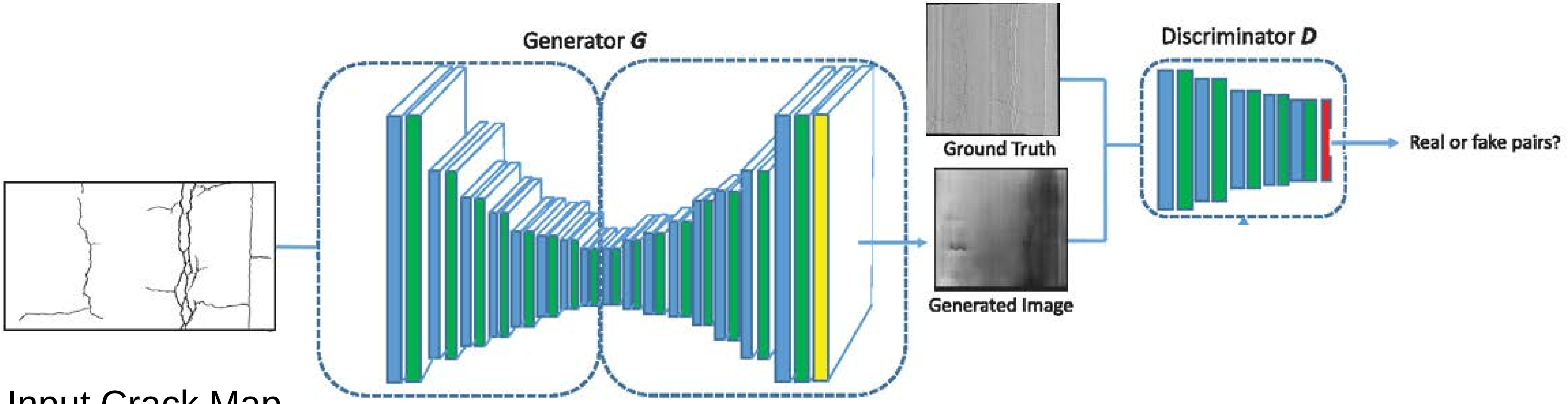
Problem Statement III

- Hard to Distinguish Patterns from the Noise Pixels from Patterns from Fine Crack Pixels
- How to Reduce the False Negative Detections



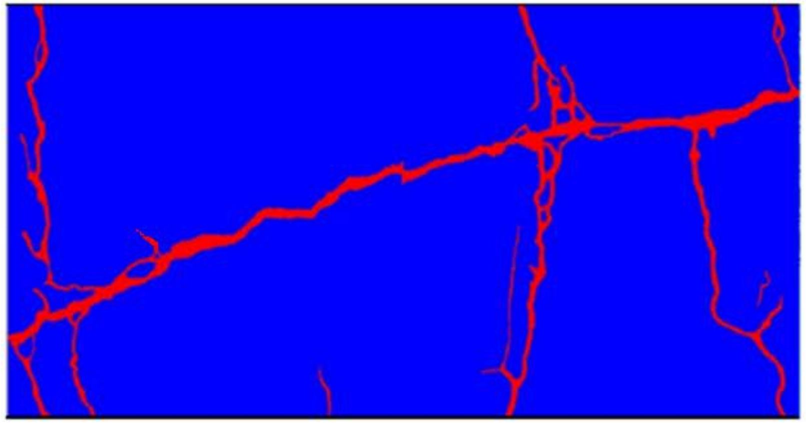
GAN Based Crack Generation

- Network Architecture

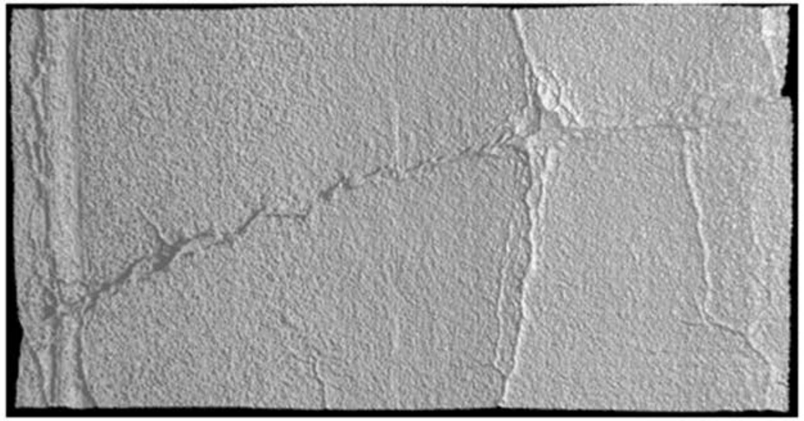


Input Crack Map

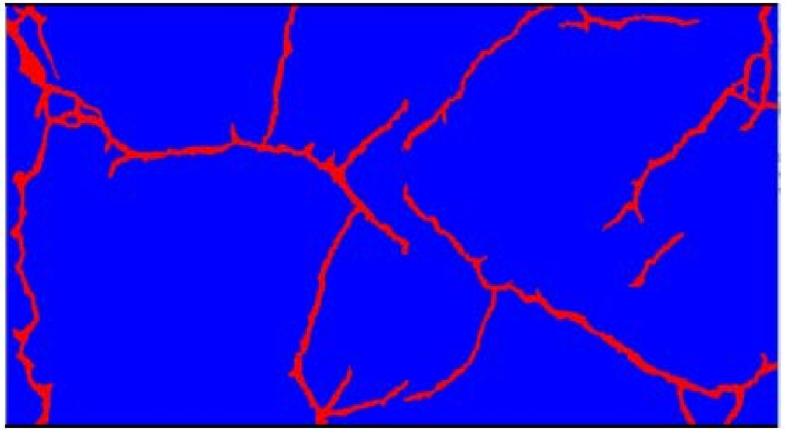
Generated Results



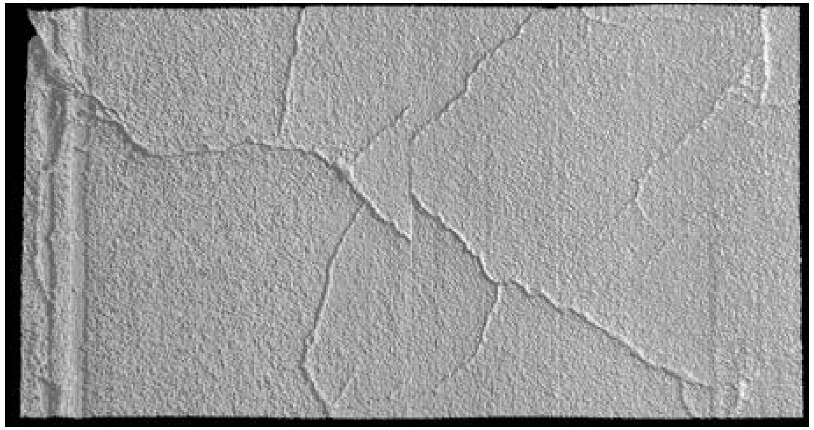
Input Crack Map



Output 3D Pavement Surface

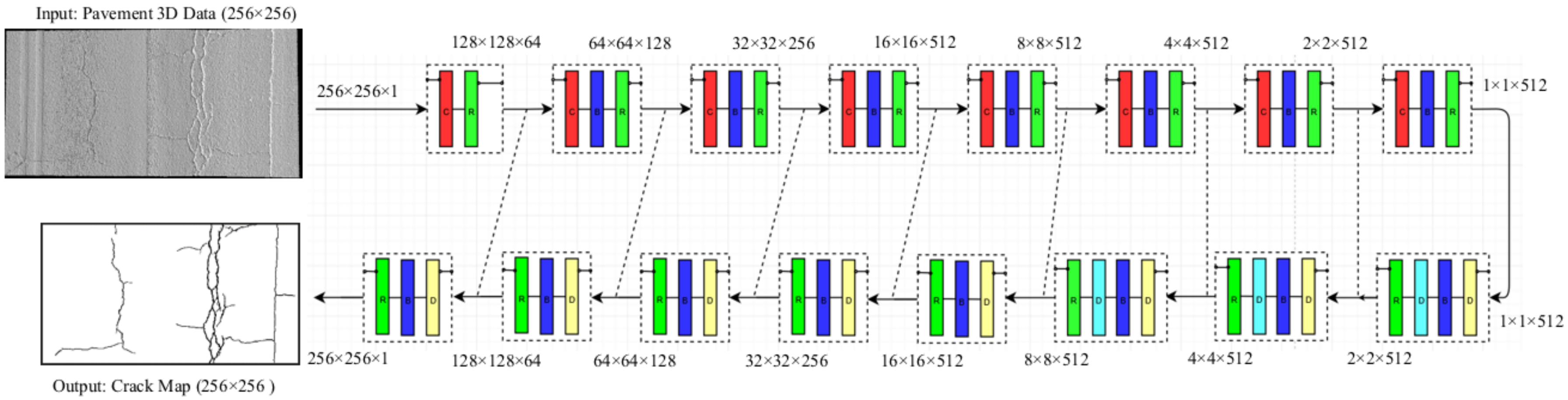


Input Crack Map

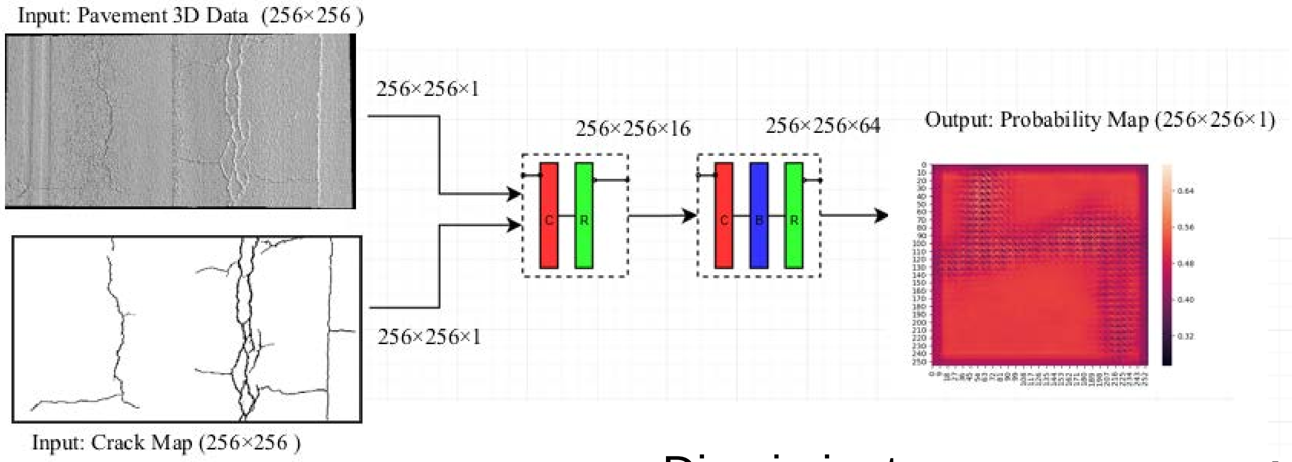


Output 3D Pavement Surface

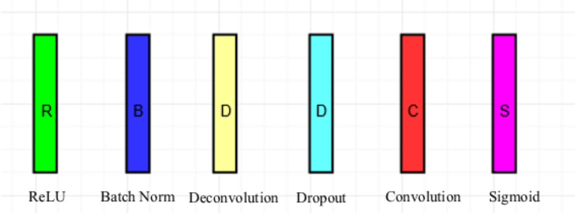
GAN Network Architecture



Generator



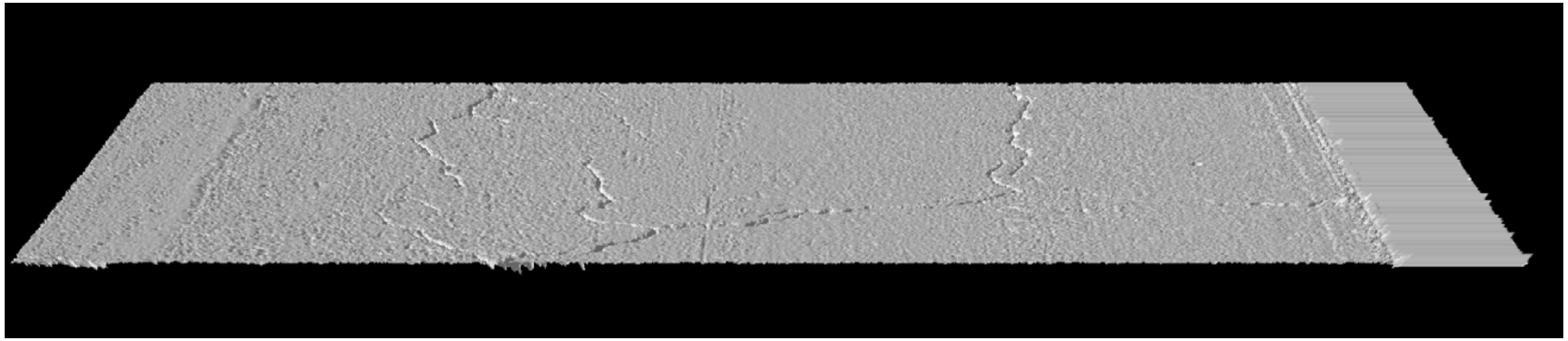
Discriminator



Meaning of Each Layer

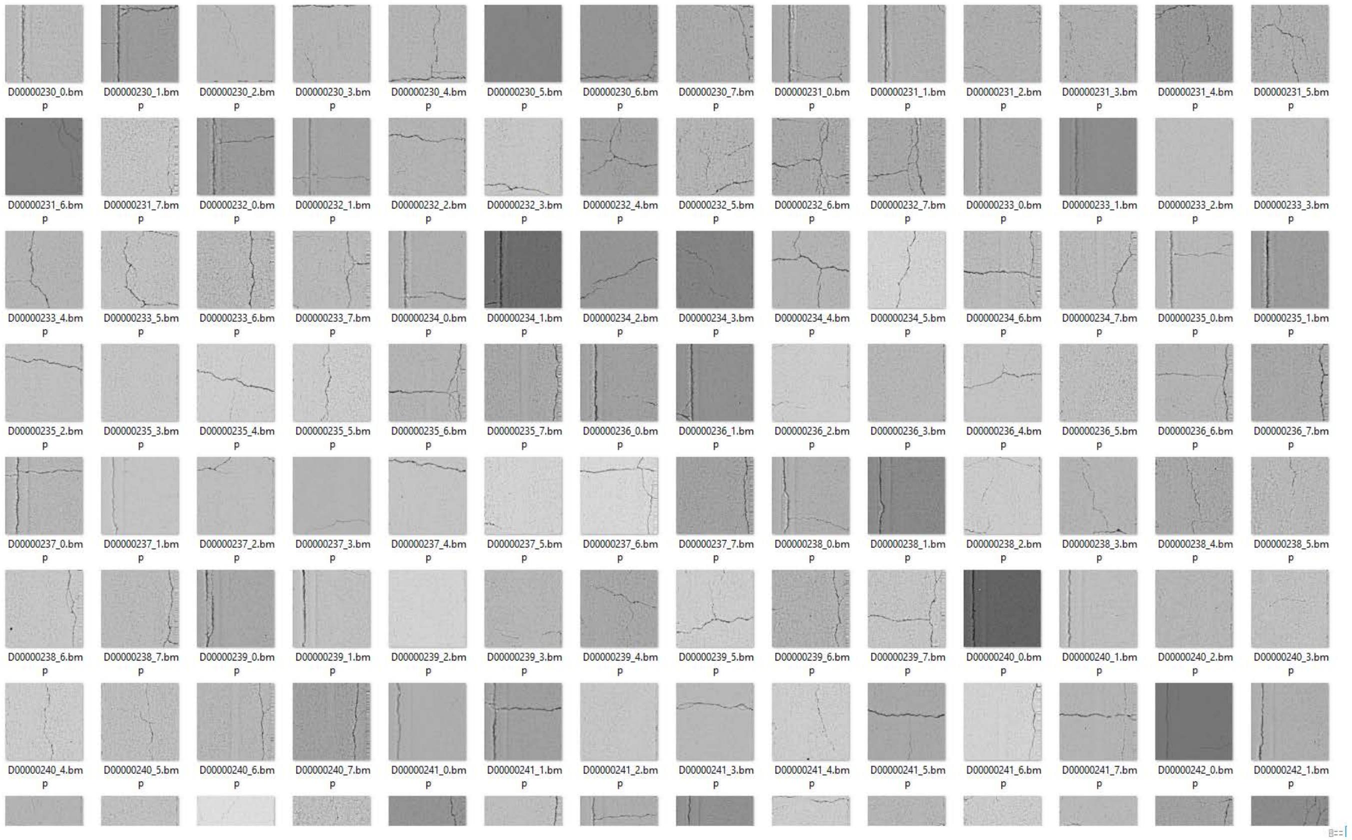
Flatten Surface for Later Processing

- Pre-Processing: Median Filter

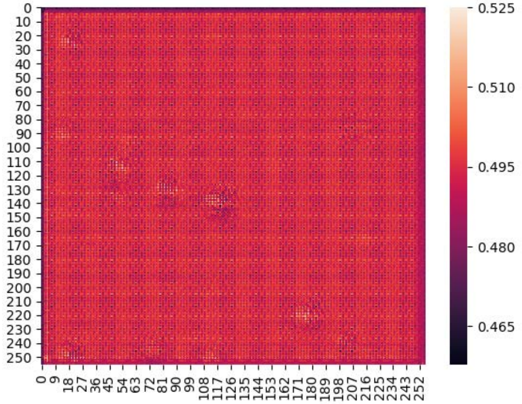


Training Data

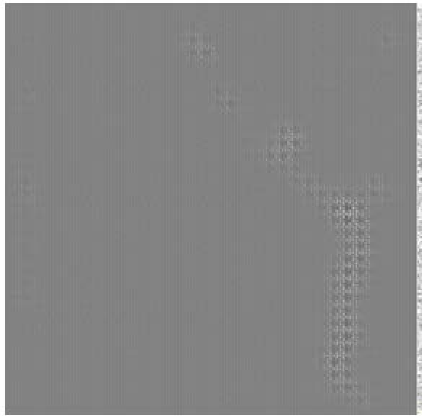
- More than 1000 Crack Images without Noise
- Hundreds Images with Noise



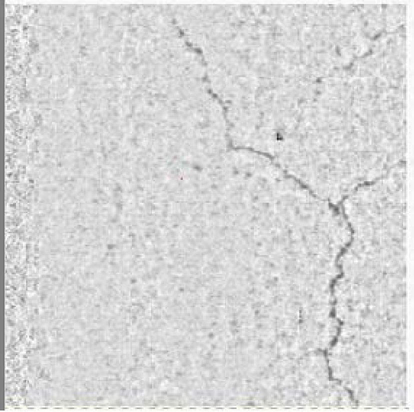
Initial Training Results



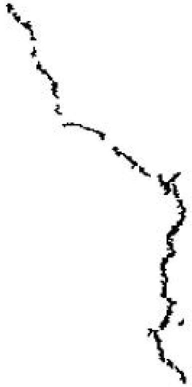
Probability Map from D



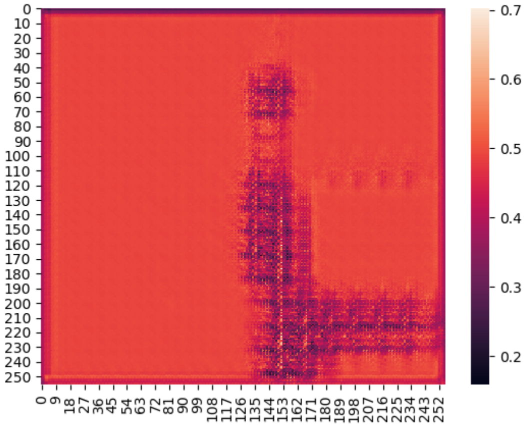
Crack Map from G



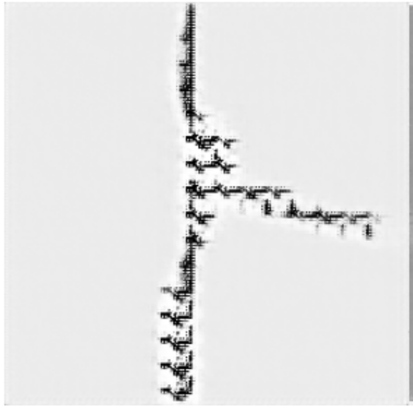
Pavement Data



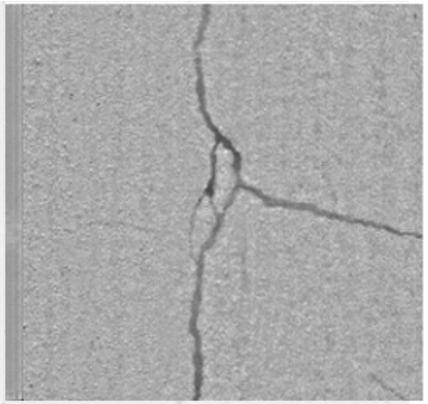
Ground Truth Crack Map



Probability Map from D



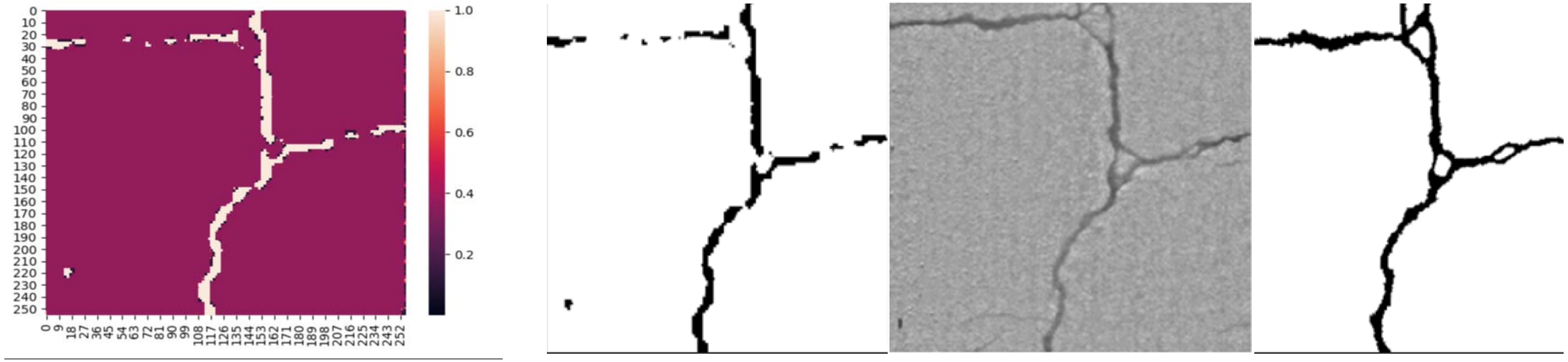
Crack Map from G



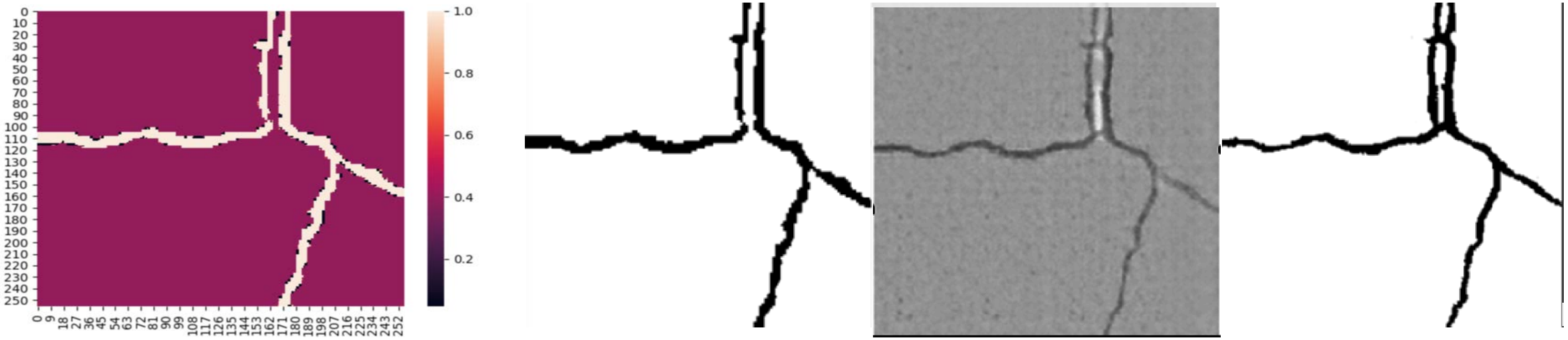
Pavement Data

Ground Truth Crack Map

Finalized Training Results



Probability Map from D | Crack Map from G | Pavement Data | Ground Truth Crack Map

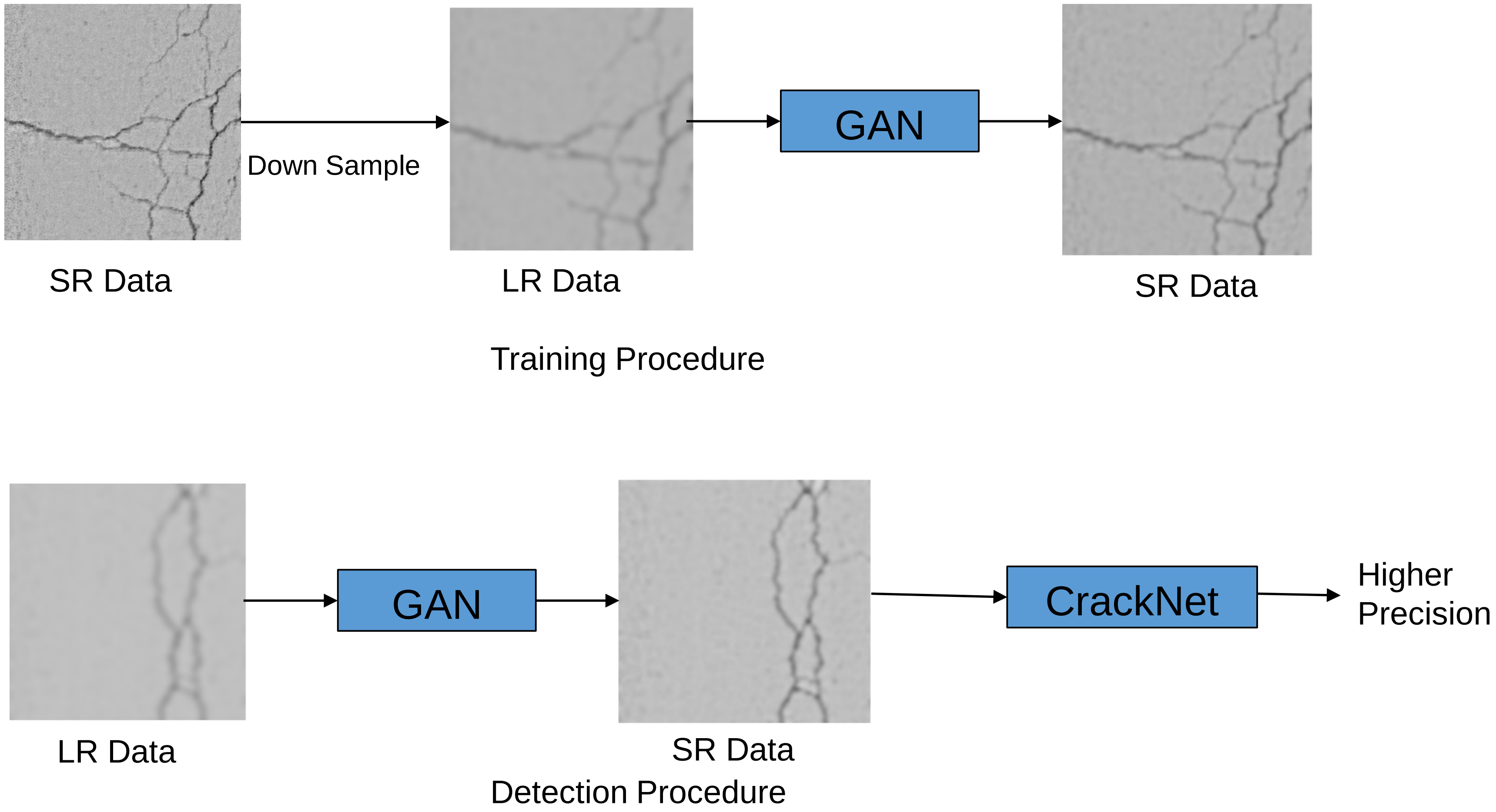


Probability Map from D | Crack Map from G | Pavement Data | Ground Truth Crack Map

GAN Based Image Quality Enhancer

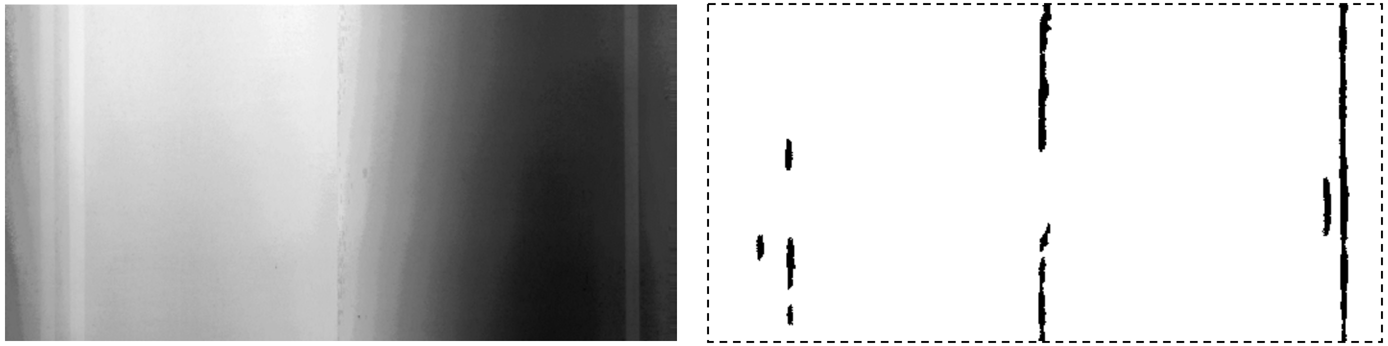
- New Ongoing Work: Generates High Resolution Data from Low Resolutions Data
  - 1 mm resolution data as the training data
  - Down sample the 1 mm resolution data to 4 mm or 16 mm resolution as the input for the GAN
  - Train the GAN to recovery the data to 1 mm resolution

Procedures

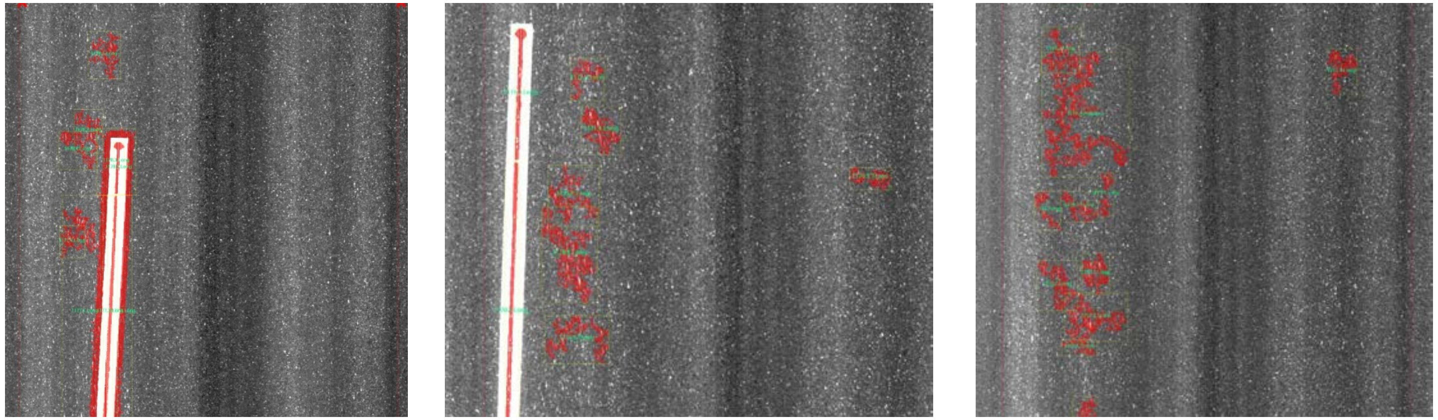

Down Sample
GAN
SR Data
LR Data
SR Data
Training Procedure
GAN
CrackNet
Higher Precision
LR Data
SR Data
Detection Procedure

Problem Statement IV

- False-Positive Results



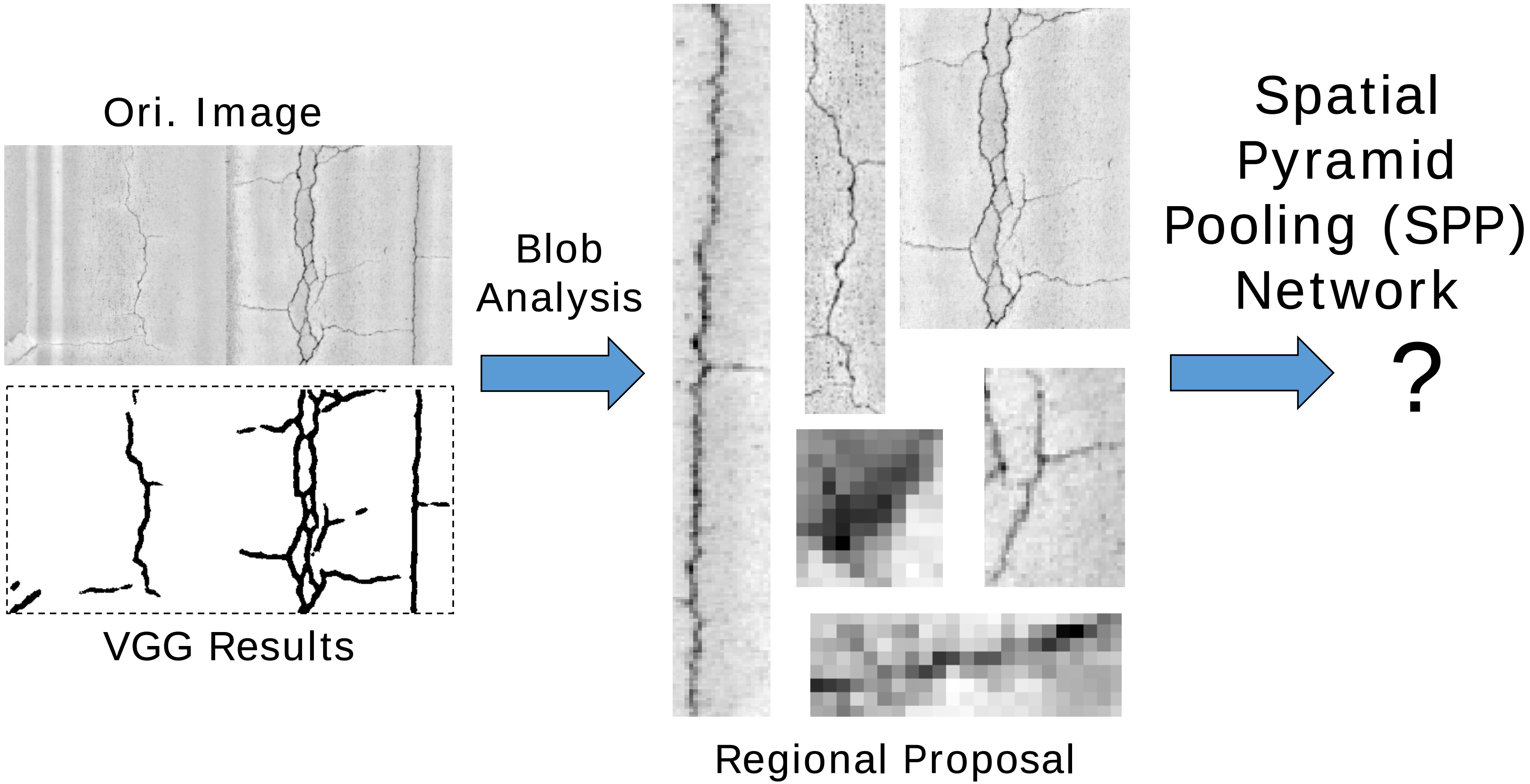
VGG Results



CrackNet-R Results

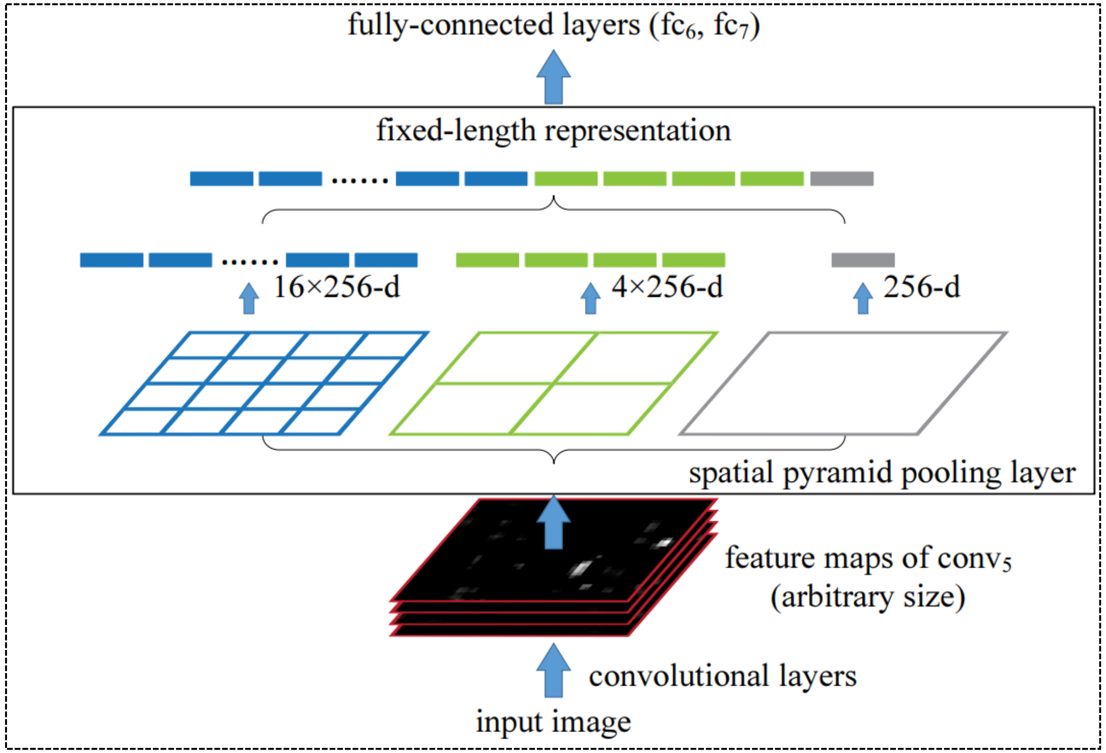
Solutions

- Pattern-Level Re-Detection



Components of SPP Network

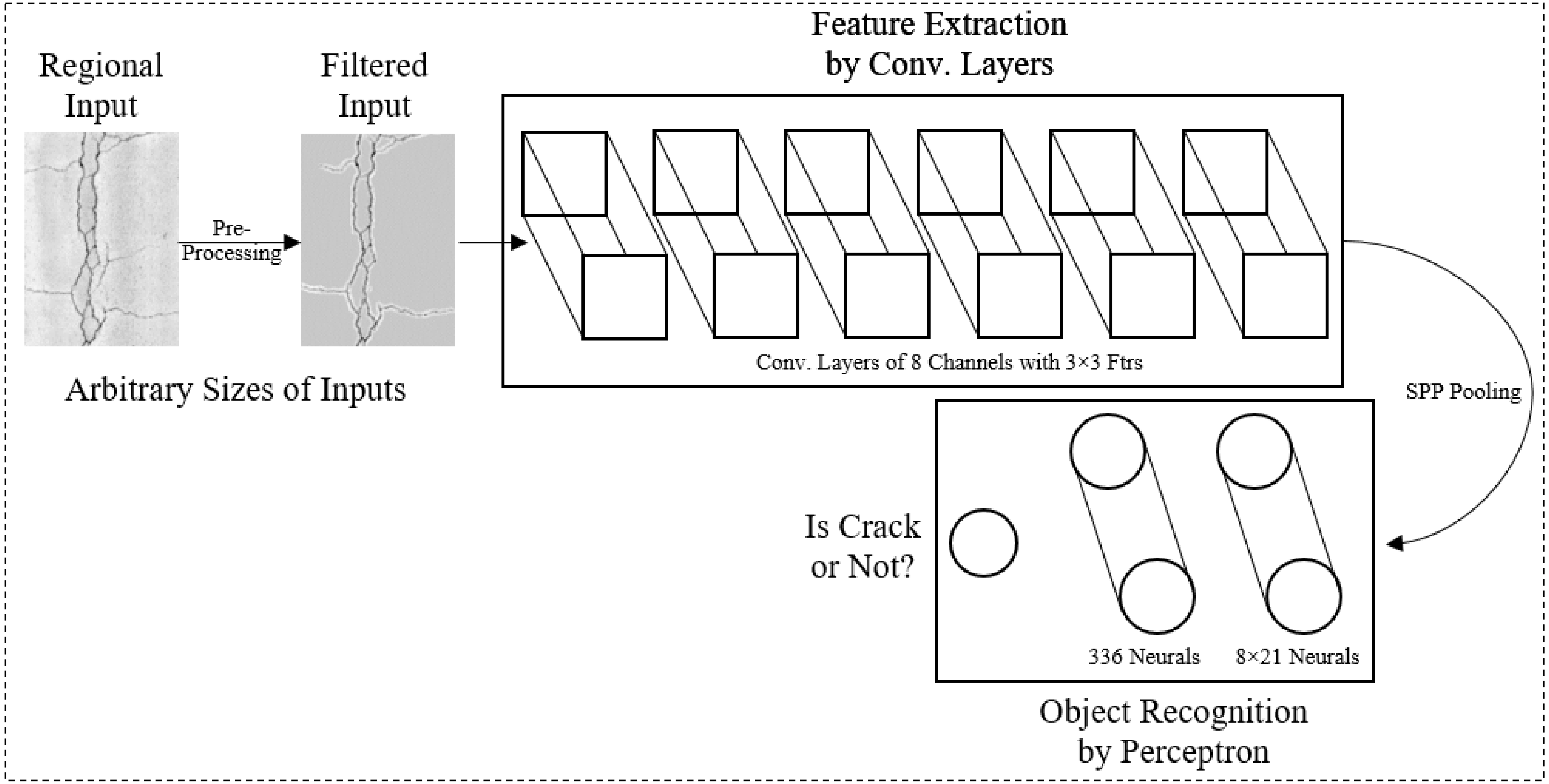
- Convolutional Layers
- Spatial Pyramid Pooling (SPP)
- Fully-Connected Layers



Fixed-Length Feature Generation Regardless of Image Sizes

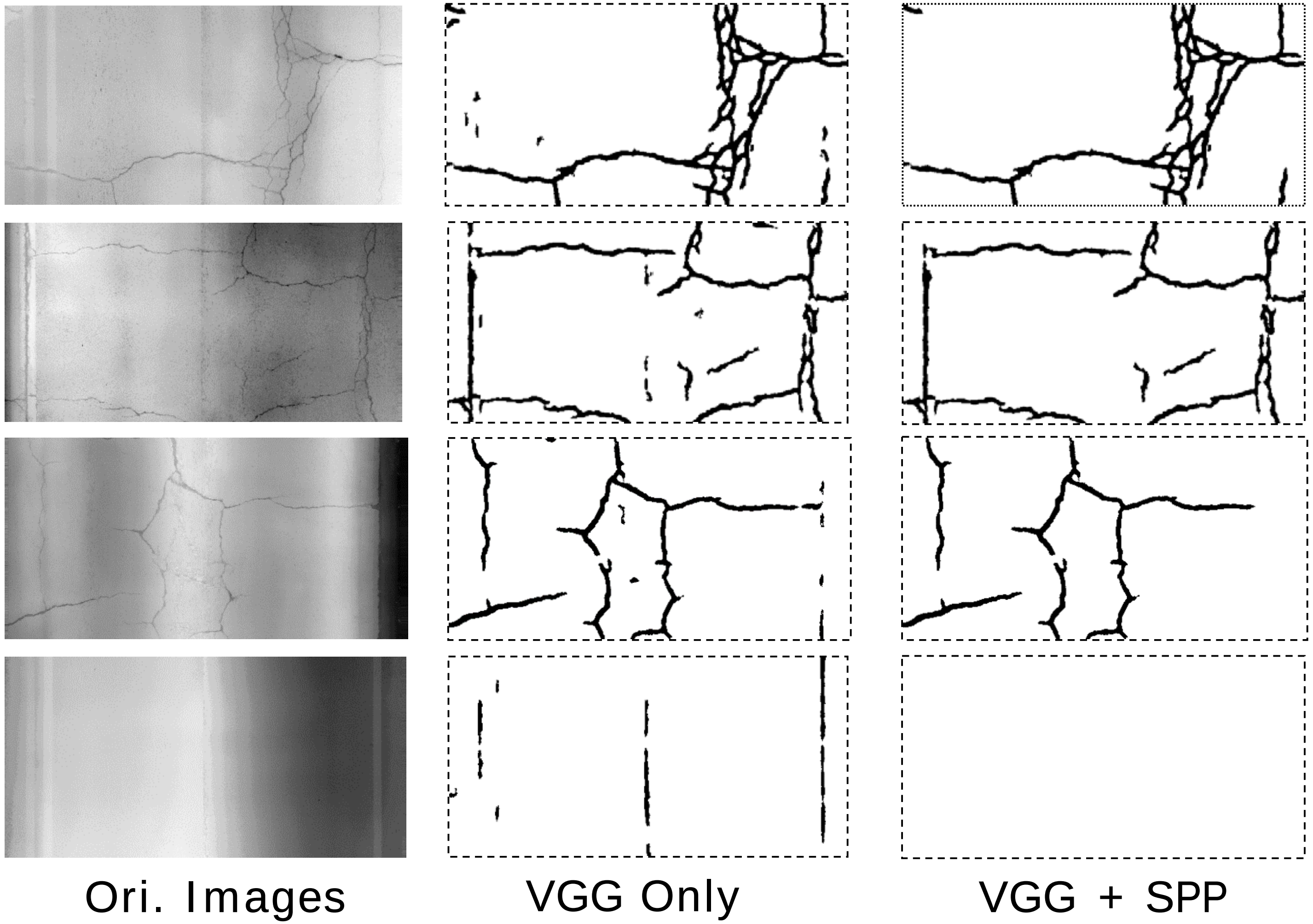
[1] "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition", Kaiming He et al., 2015

SPP based Crack Detection



Experimental Results

❑False-Positive Suppression



Experimental Results

❑Performance Indices Comparison

	Precision	Recall	F-Measure
VGG (Tanh)	84.31	90.12	87.12
VGG + SPP	90.76	89.38	90.06

❑Summary

- ❑ Recall: Slightly Decrease
- ❑ Precision: Largely Increase
- ❑ F-Measure: Achieve 90.06

❑ SPP Speed

- ❑ i7-4810MQ + GTX 980M
- ❑ 0.23 Sec. / Image

Next-Gen Sensors: 1mm & 0.1mm in 3D

- Components in Laser Electronics & Imaging
  - Evolving Rapidly
  - 2K (2048-pix), 4K (4096-pix), & 8k (8192-pix)
  - High-frame rates
  - Affordable high-power laser
  - Computing (CPU, GPU), & Newer Hardware Interfaces
- Result
  - Better Quality at Higher Performance

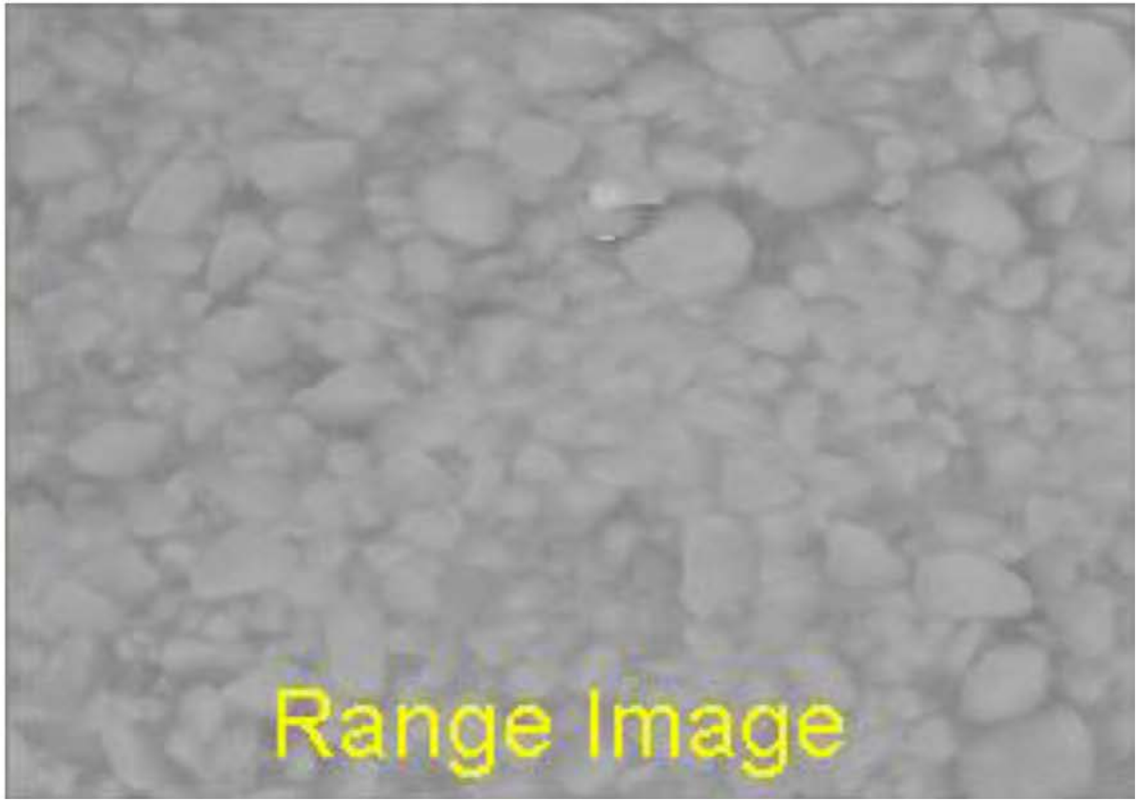
Challenges in Pavement Safety Data

- Decades Old Approaches
  - Micro & Macro Texture Data Sets; MPD, MTD?
  - Contact & Water Based Friction Devices
  - Aging Standards: ASTM et al
- Data Quality
  - Comparable?
  - Consistent?
  - Precision & Bias Levels?
- High Cost
  - Equipment Capital
  - Operation

Non-Contact 0.1mm 3D Sensor

- Laser & Electronics Limitations
  - Not Much Anymore
- Computing & Interface Performance
  - Timely
- Challenges
  - Ongoing R&D for Highway Speed
  - Validation & Verification Against Traditional Means
- Objectives
  - Ultimately replace both texture measurement sensors & contact-based friction devices

Samples of Sub-0.1mm 3D Data (LS-40)



Lessons Learned

- Deep Learning
  - Truly Useful for Cognition Based Problems
  - Unparalleled Field Applications in Recent Years
- Fully Automated Cracking System
  - Achieved First-Time Ever with CrackNet in 2018
  - 60MPH (100KPH) Processing Speed in 2019?
- Other Pavement Applications
  - Safety Measurement of Pavement Surfaces
  - Other Non-Cracking Distresses

Where does the Future Lead?

- ❑DL Solutions Applicable to Infrastructure based Problems
- ❑Highway/Runway/Tunnel/High-Speed Rail
- ❑Very Fortunate: New Sensors, Software Tools & Computing Capabilities
- ❑**Self-Learning**
- ❑**Very Large Training Data Sets: 20,000 Pairs**

Conclusions

- Deep Learning (DL) Based Solutions
  - Strong capabilities of learning
  - Consistent precision and bias levels on any roads/runways
  - Better with deeper structures & larger data sets
- CrackNet: Consistent Efficiency in Pixel Accuracy
- A Future for Automated Surveys
  - Non-Analytical, Intelligence Based Solutions