Pavement Distress Detection Using Advanced Machine Learning Methods with Intensity and Depth Data

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Fugro Roadware

Fugro Roadware


- Founded in 1969
- 1st fully integrated road data collection vehicle (ARAN) in 1980
- 2019
  - 56 ARANs operating in 18 countries
  - Over 10 Million miles of ARAN roadway data to date
  - Over 500 Thousand miles of ARAN roadway data each year

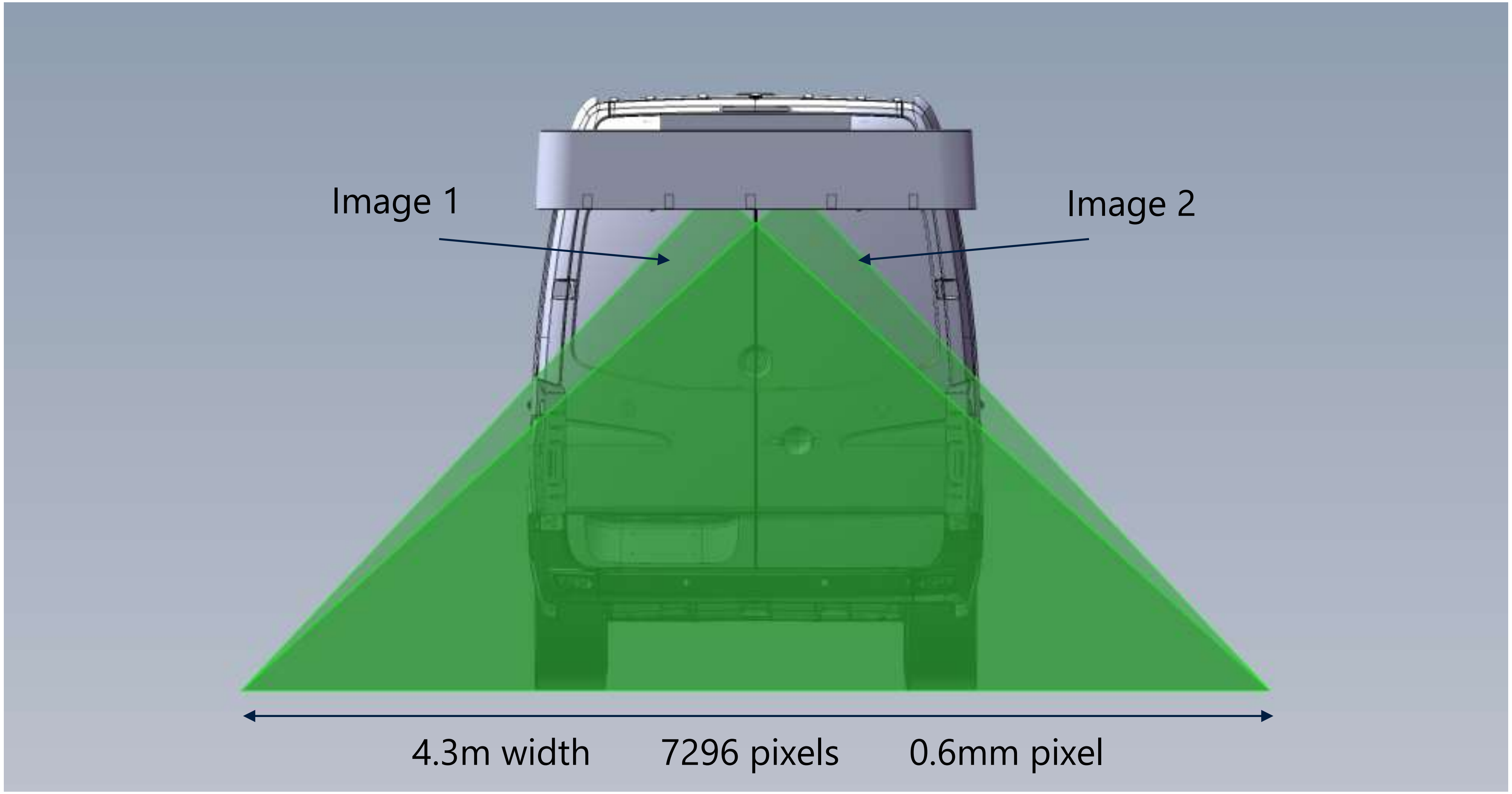
Overview

- Why develop crack detection algorithms?
  - Automation increases value of pavement data:
    - Less human intervention = less subjectivity = more dependable results
    - Faster results = more time to use the data = better decisions
  - Current automated algorithms aren’t good enough

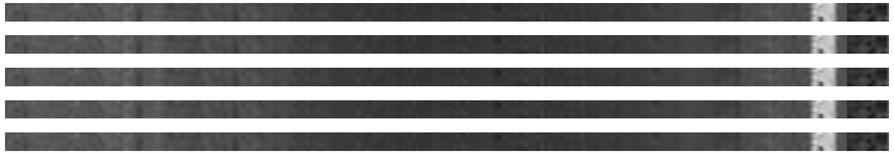
- Why Machine Learning?
  - Rapidly improving field
  - Excellent at solving complex problems with unstructured data

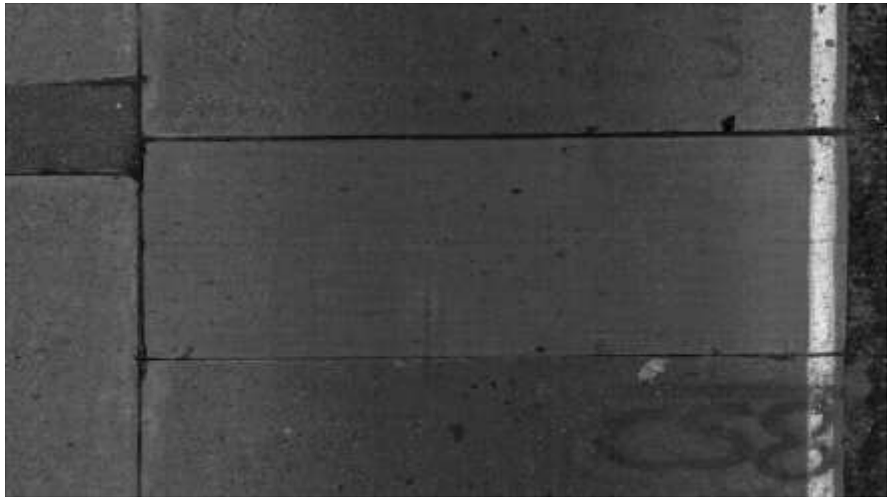
- Why us?
  - We have 50 years of experience in pavement condition analysis
  - We have a lot of accessible pavement data = 3 PetaBytes = 2 Million Miles
    - …and it is already annotated

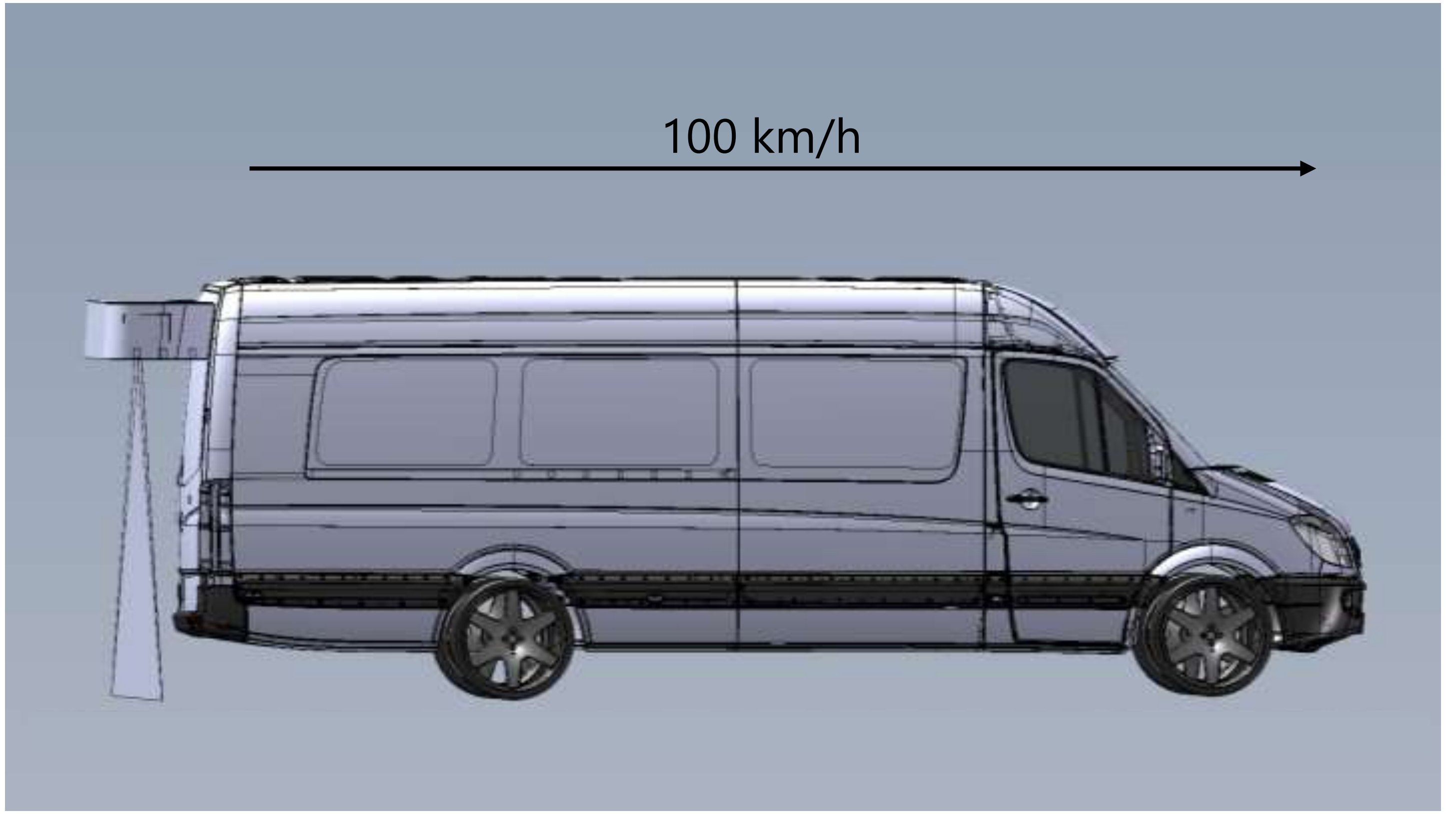
Pave3DX Stereoscopic Imaging and Measurement



1mm Lines Combined into Image Frames







2 Images from different angles

Image 1 (Left)

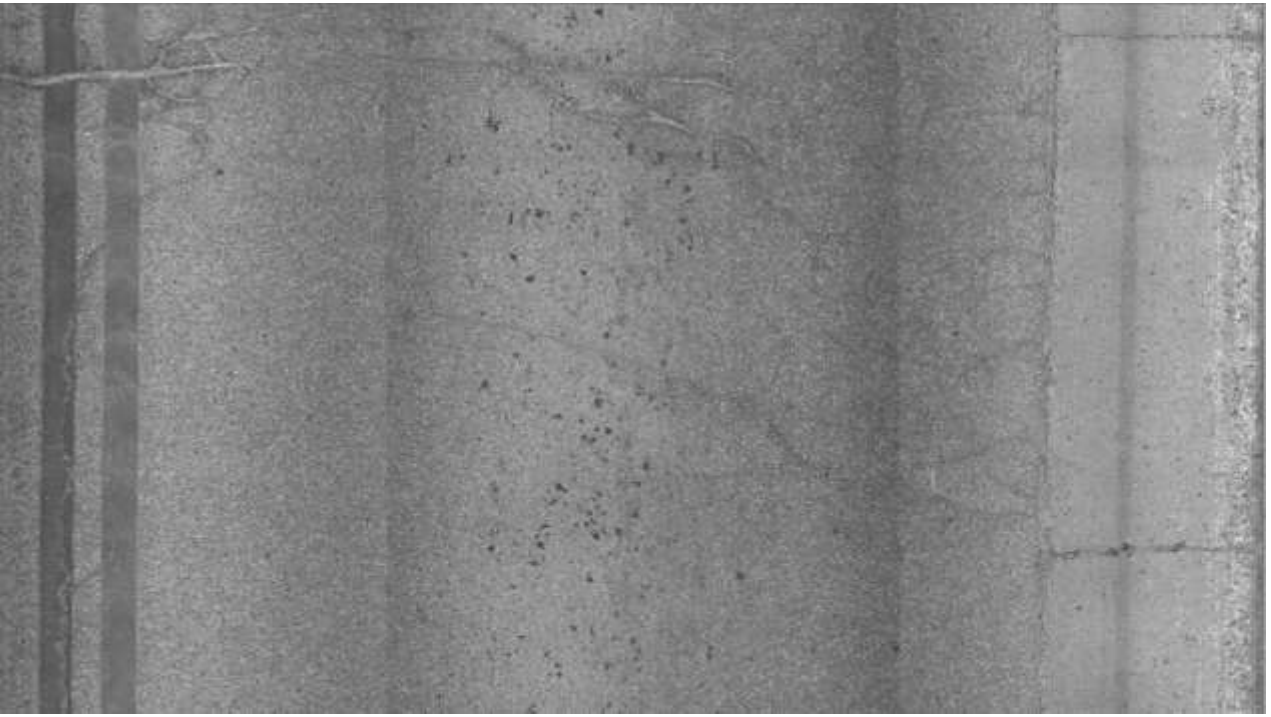
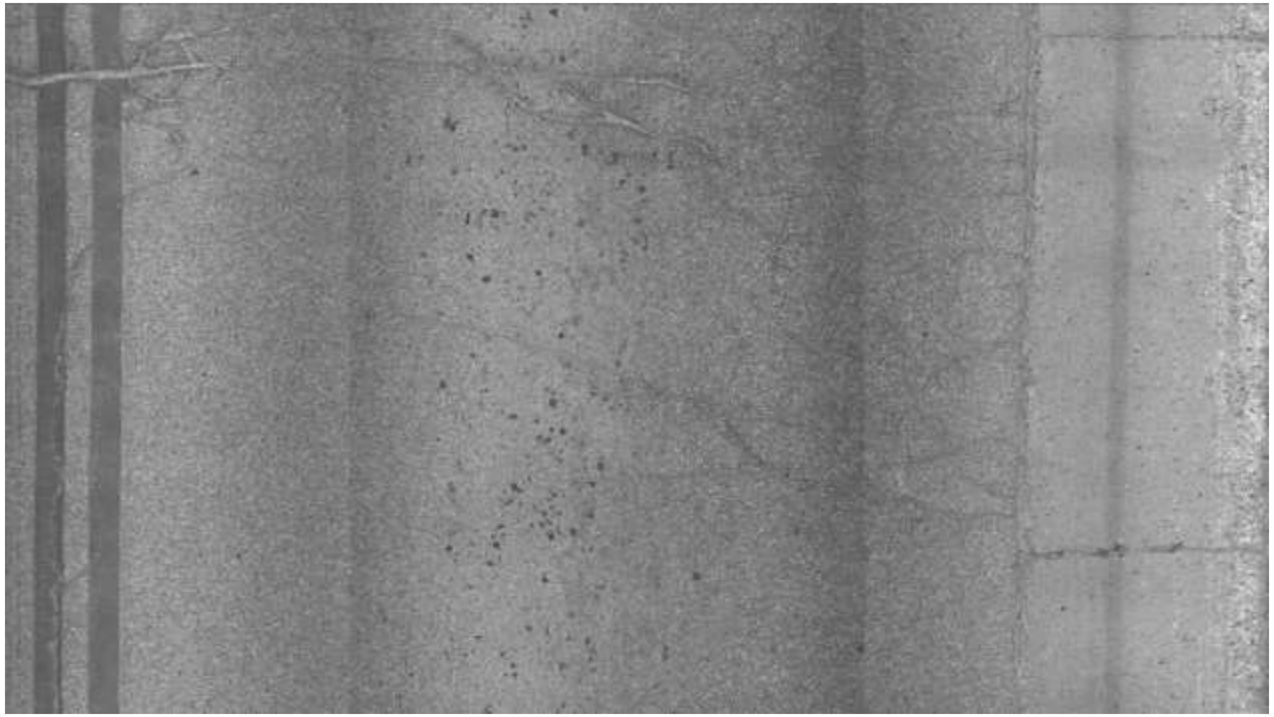


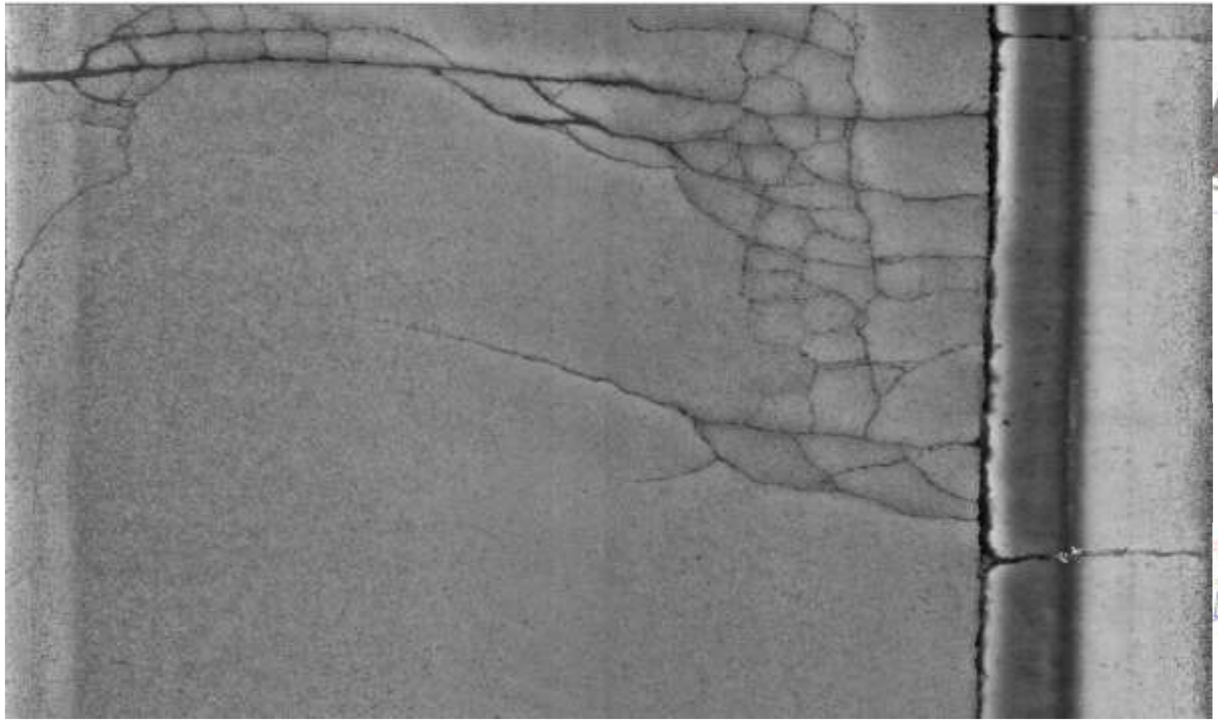
Image 2 (Right)

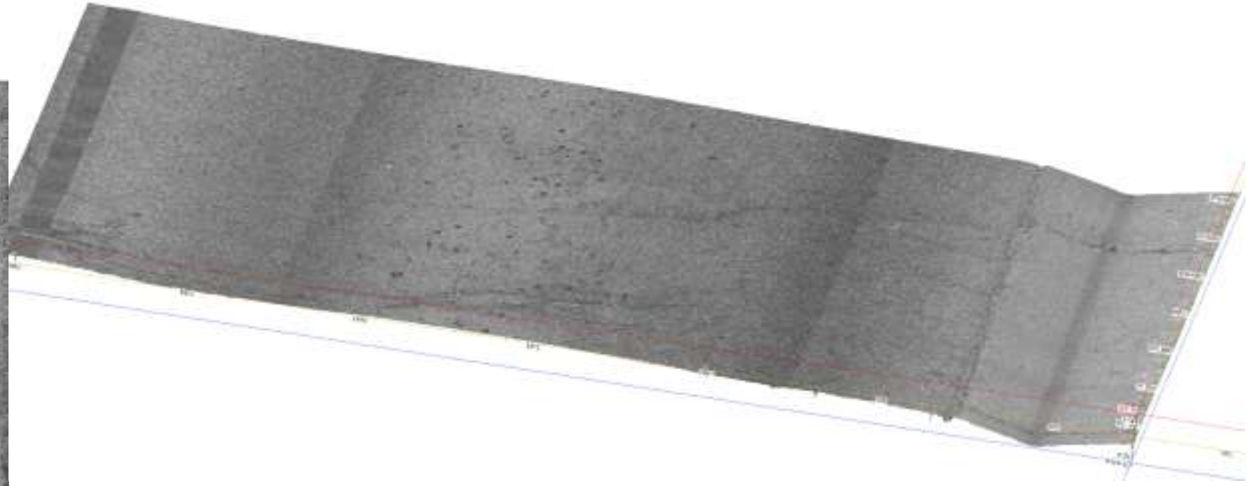


Combine Stereo Images

3D Model

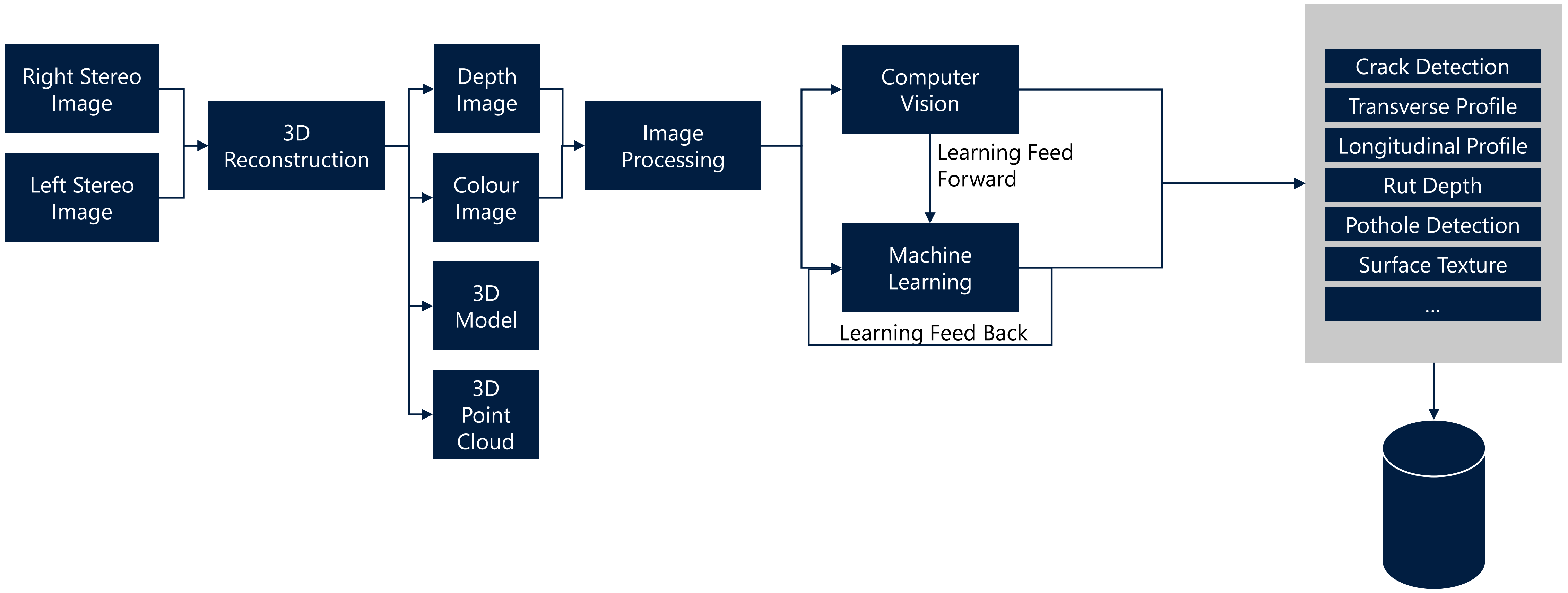
Depth Image





3D Point Cloud

Pave3DX + WiseCrax Processing Pipeline



WiseCrax Detection Pipeline

Noise removal (autoencoder)

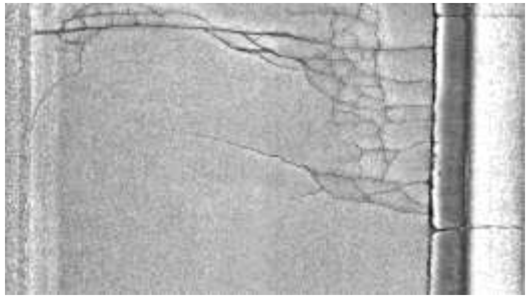
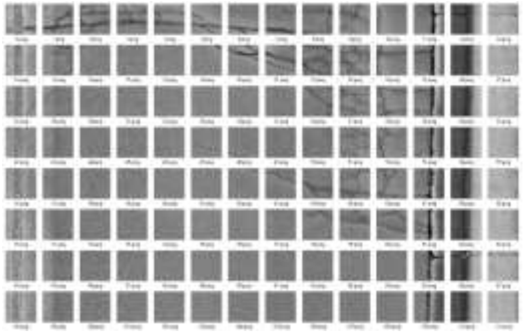


Image tiles



Supervised

Unsupervised

Keras

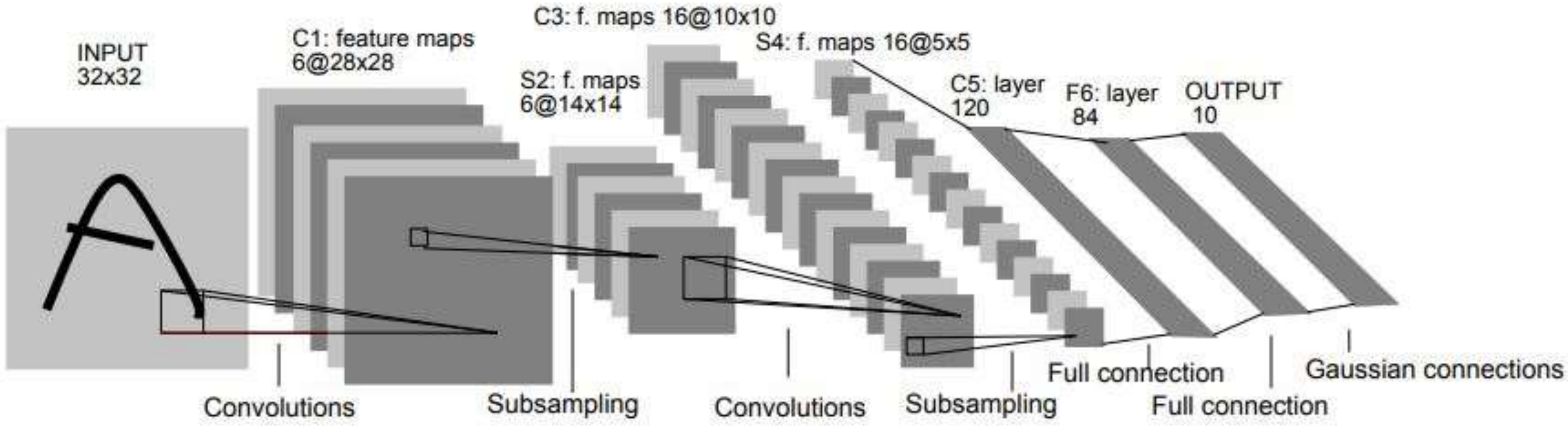
ML model

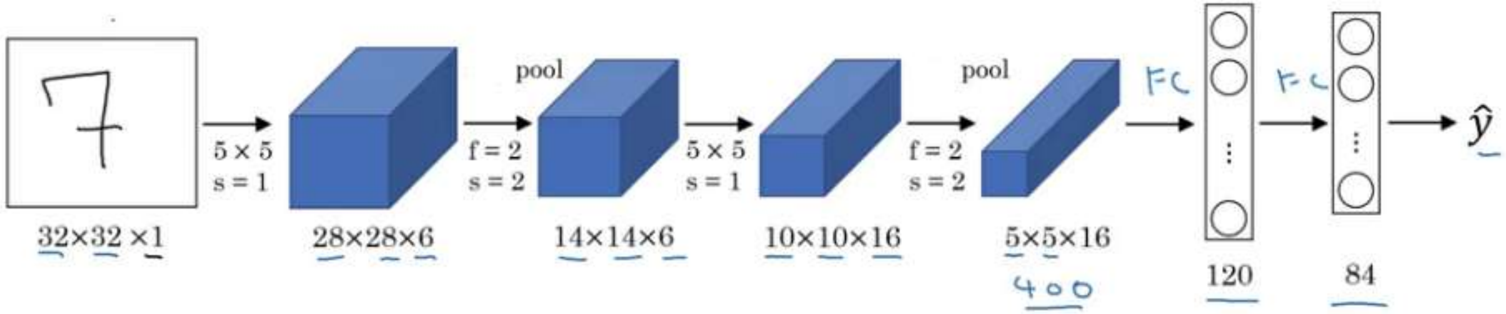
aws

DB

Roadware Vision

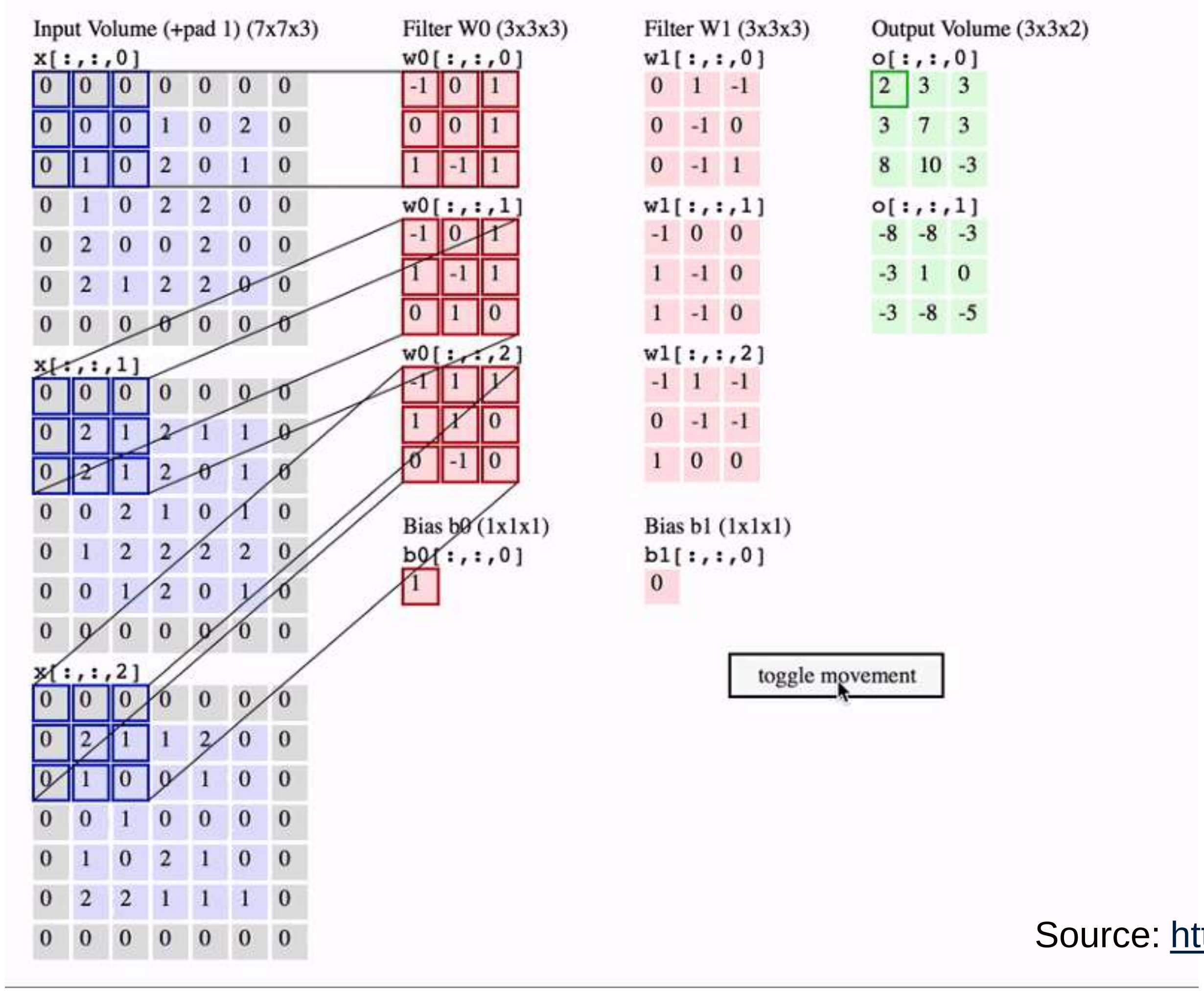
LeNet-5 – A Classic CNN Architecture





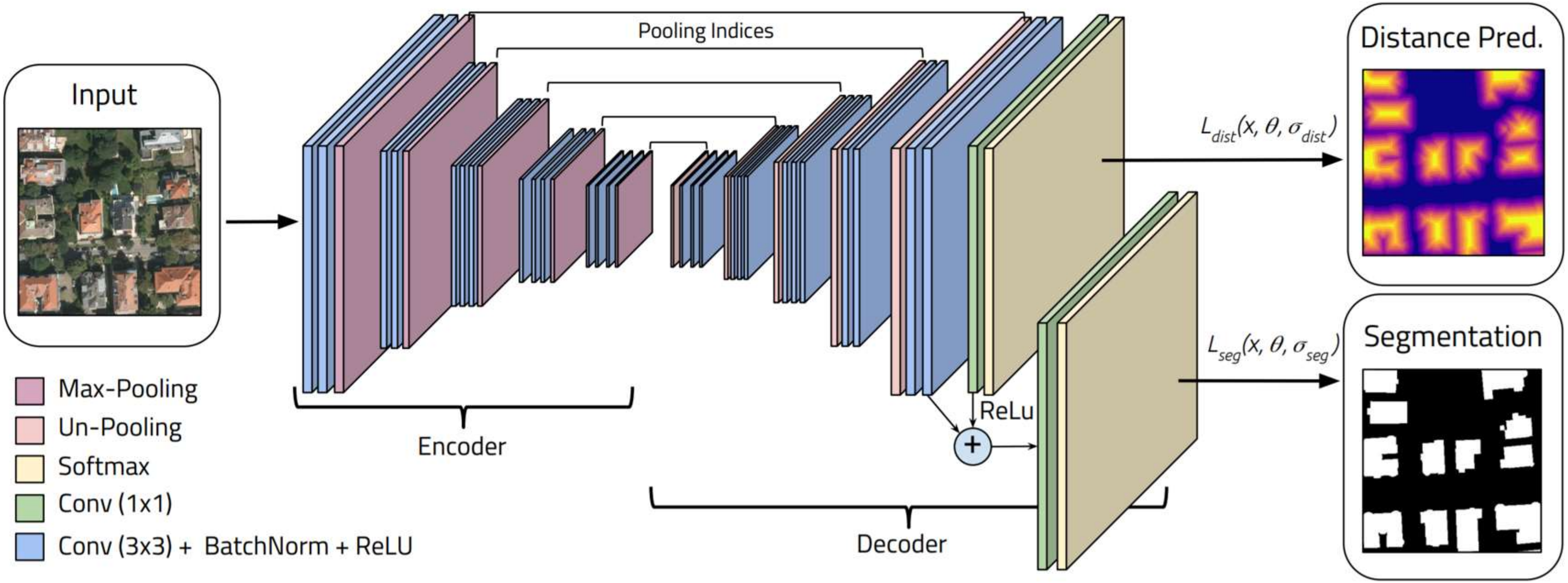
http://yann.lecun.com/exdb/publis/pdf/lecun-98.pdf

Convolution Operation

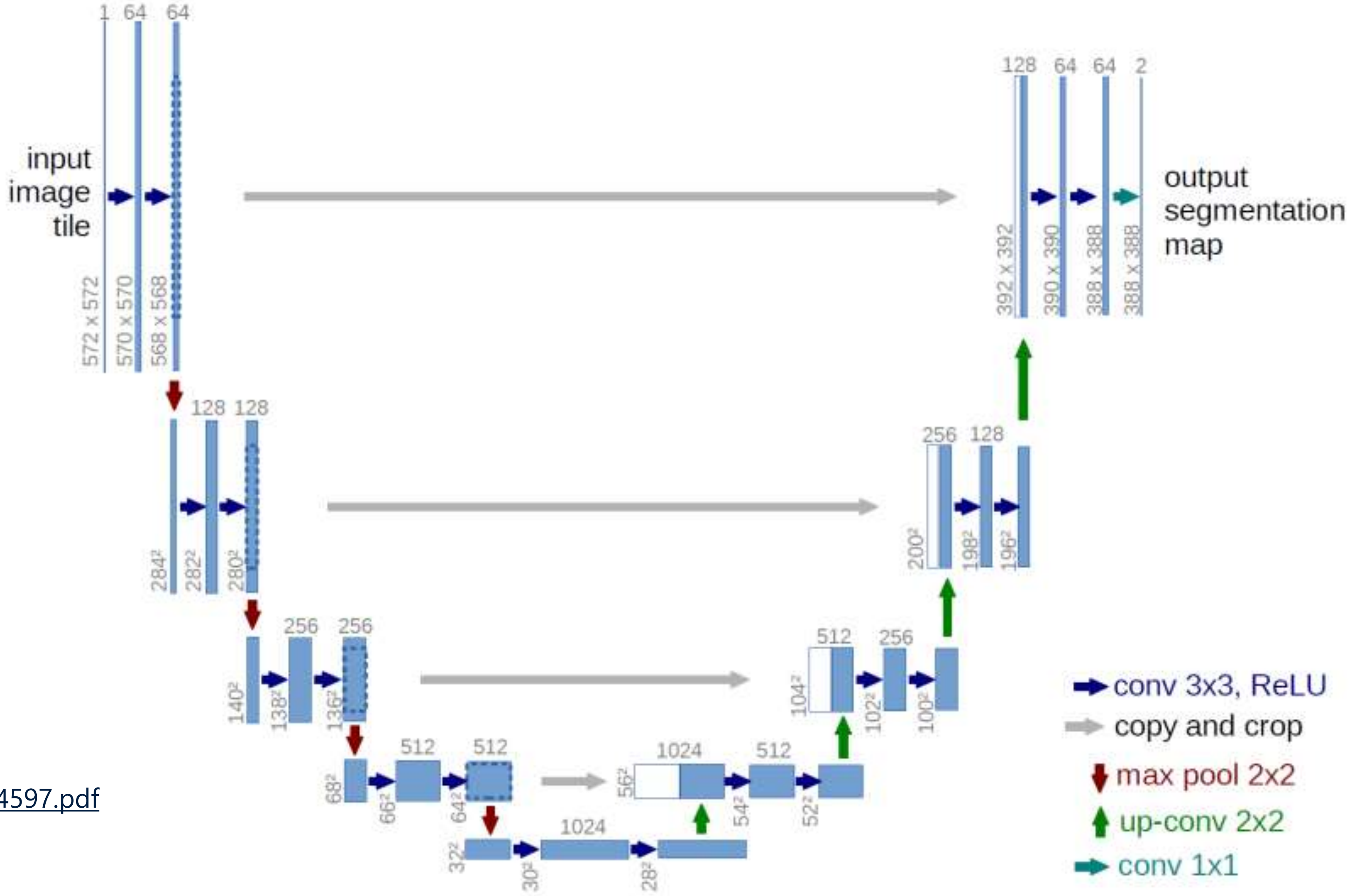


Source: http://cs231n.github.io/convolutional-networks/

Instance Segmentation



U-Net: Convolutional Networks



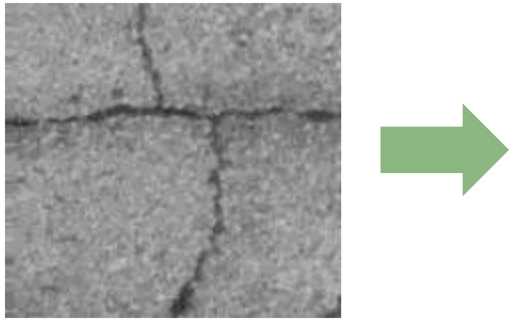
https://arxiv.org/pdf/1505.04597.pdf

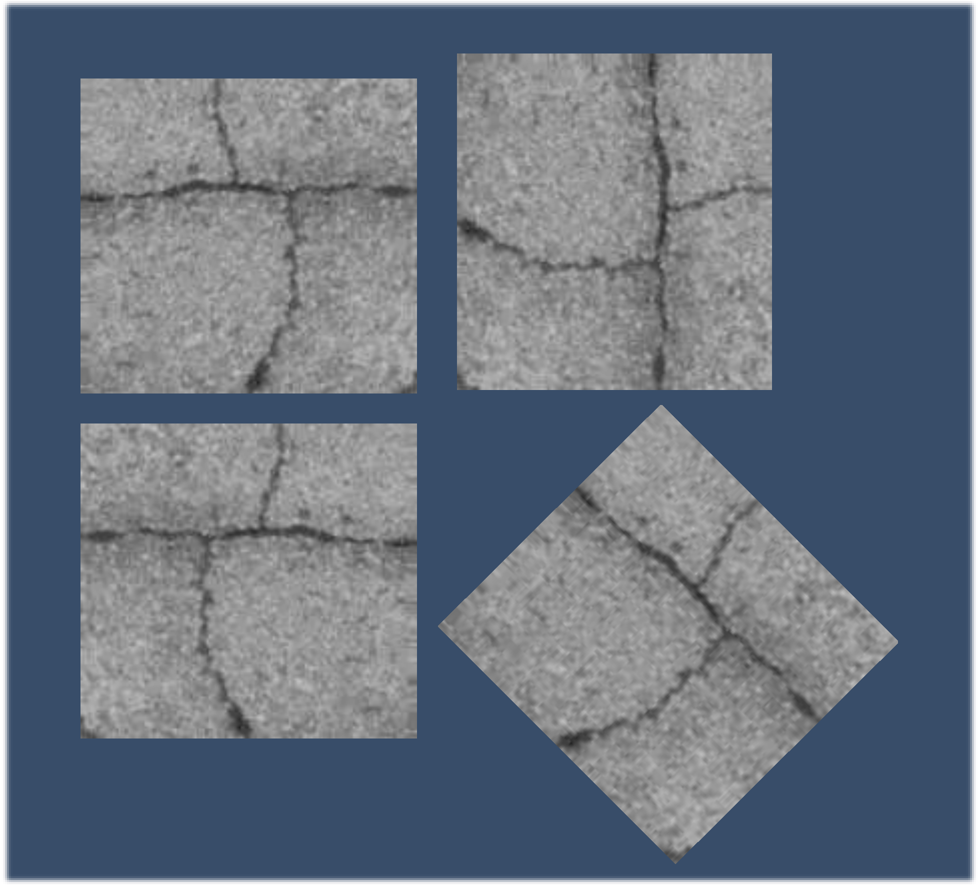
Data Augmentation

- Generate batches of image data with real-time data augmentation
- The data will be looped over (in batches)

- 250,000 images as Data Augmentation

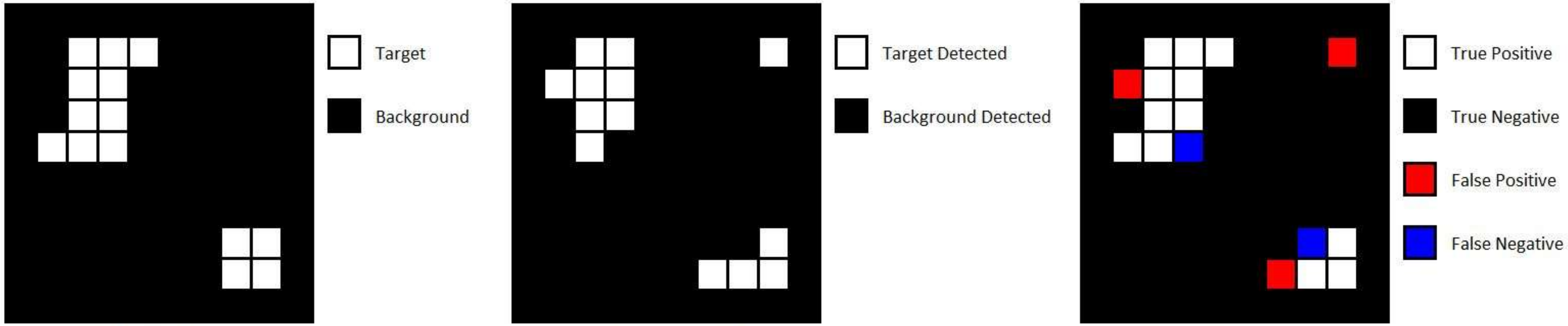
- Transformations applied:
  - Rotation
  - Flip
  - Translation
  - Gaussian Noise
  - Scale
  - Mirroring





Measure similarity between two images:

Modified Pixel-wise-based Method



(a) Ground Truth (b) Detection Result (c) Detection Performance

1. Introduce buffer regions by applying erosion on the original crack map
2. Convert the 'thick crack line' to 1-pixel-wide crack line using Skeletonization

Accuracy = Skeleton of TP / Skeleton of Union

Detection Performance Definitions

	Detected Something	Something Actually is There	Result
True Positive	YES	YES	GOOD
True Negative	NO	NO	GOOD
False Positive	YES	NO	BAD
False Negative	NO	YES	BAD

Crack Detection Metrics - Precision

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$= \frac{True\ Positive}{Total\ Predicted\ Positive}$$

Average : 0.909

		Predicted	
		Negative	**Positive**
Actual	**Negative**	True Negative	False Positive
	Positive	False Negative	True Positive

Crack Detection Metrics - Recall

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$= \frac{True\ Positive}{Total\ Actual\ Positive}$$

Average : 0.999

		Predicted	
		Negative	**Positive**
Actual	**Negative**	True Negative	False Positive
	Positive	False Negative	True Positive

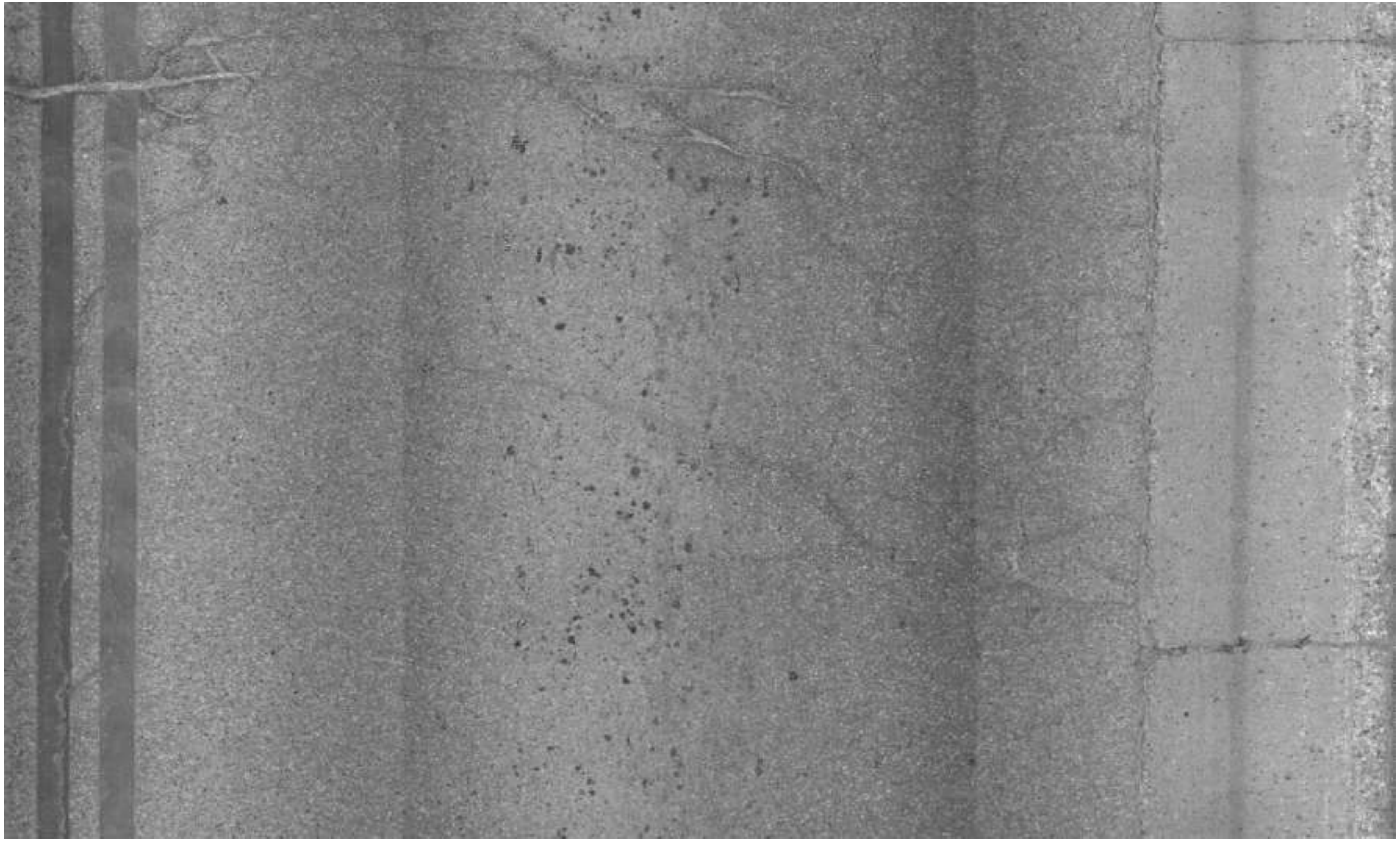
Crack Detection Metrics – F1 Score

$$F1 = 2 \times \frac{Precision * Recall}{Precision + Recall}$$

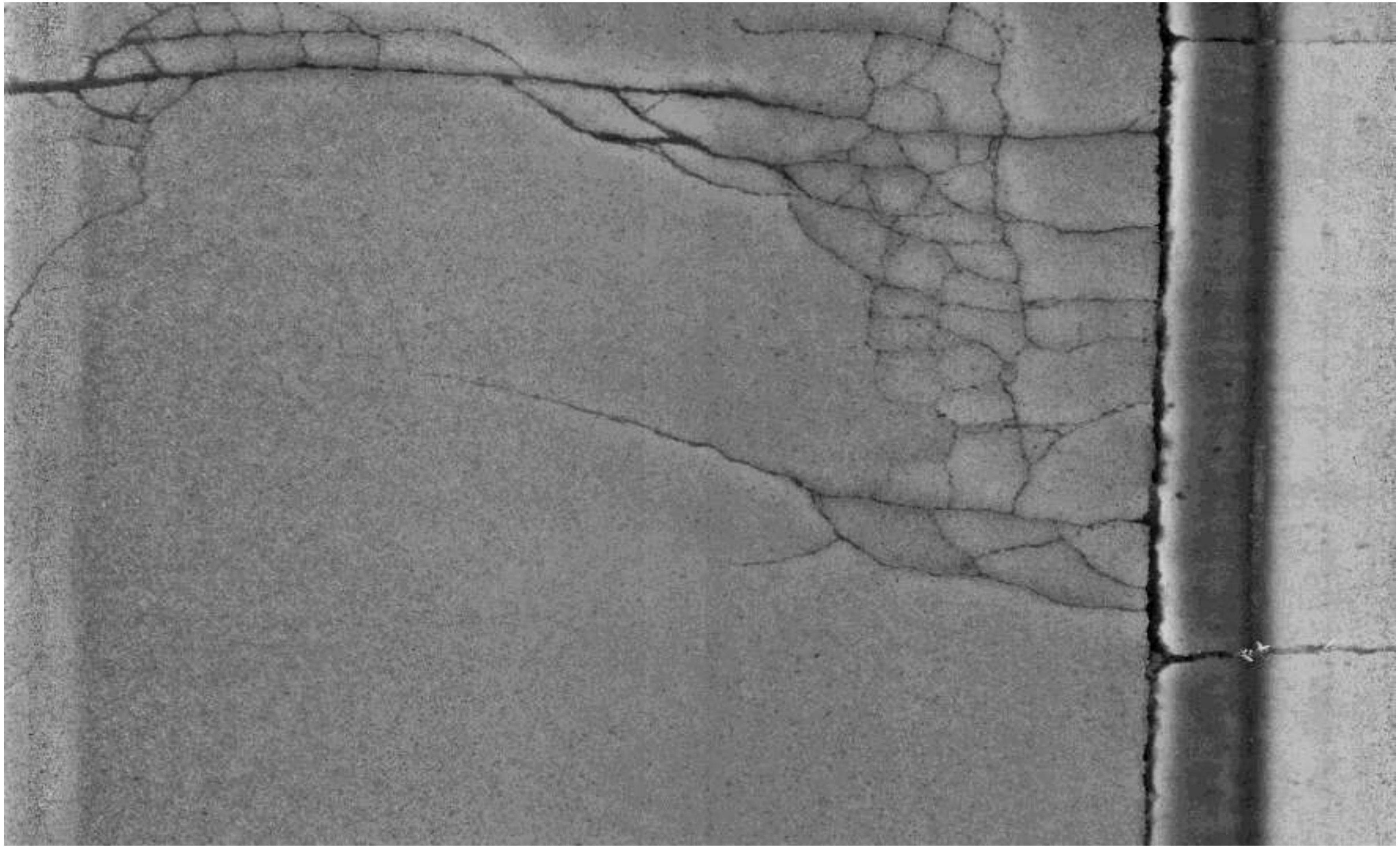
Average: 0.948

FUGRO

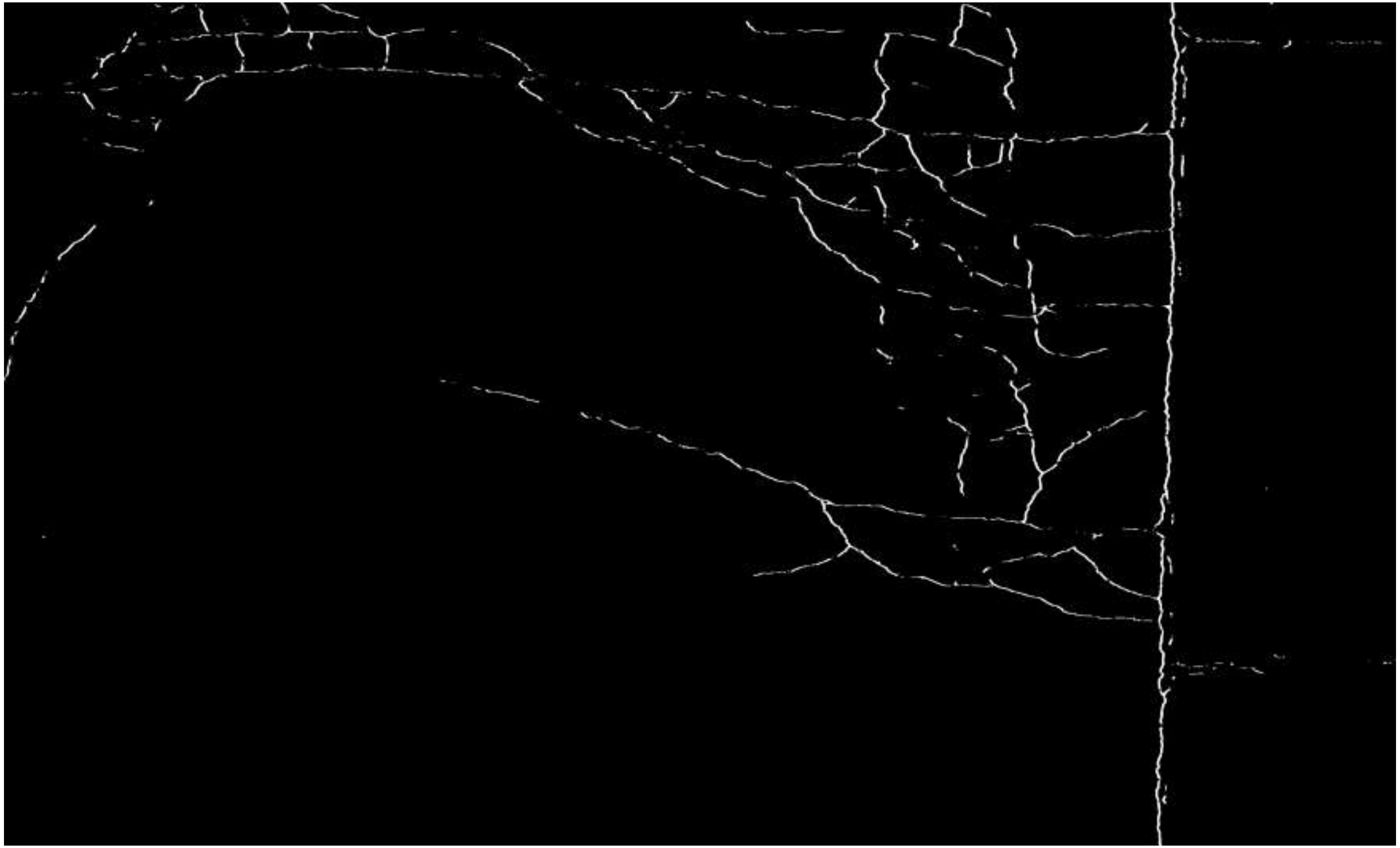
Example 1 – Real Image



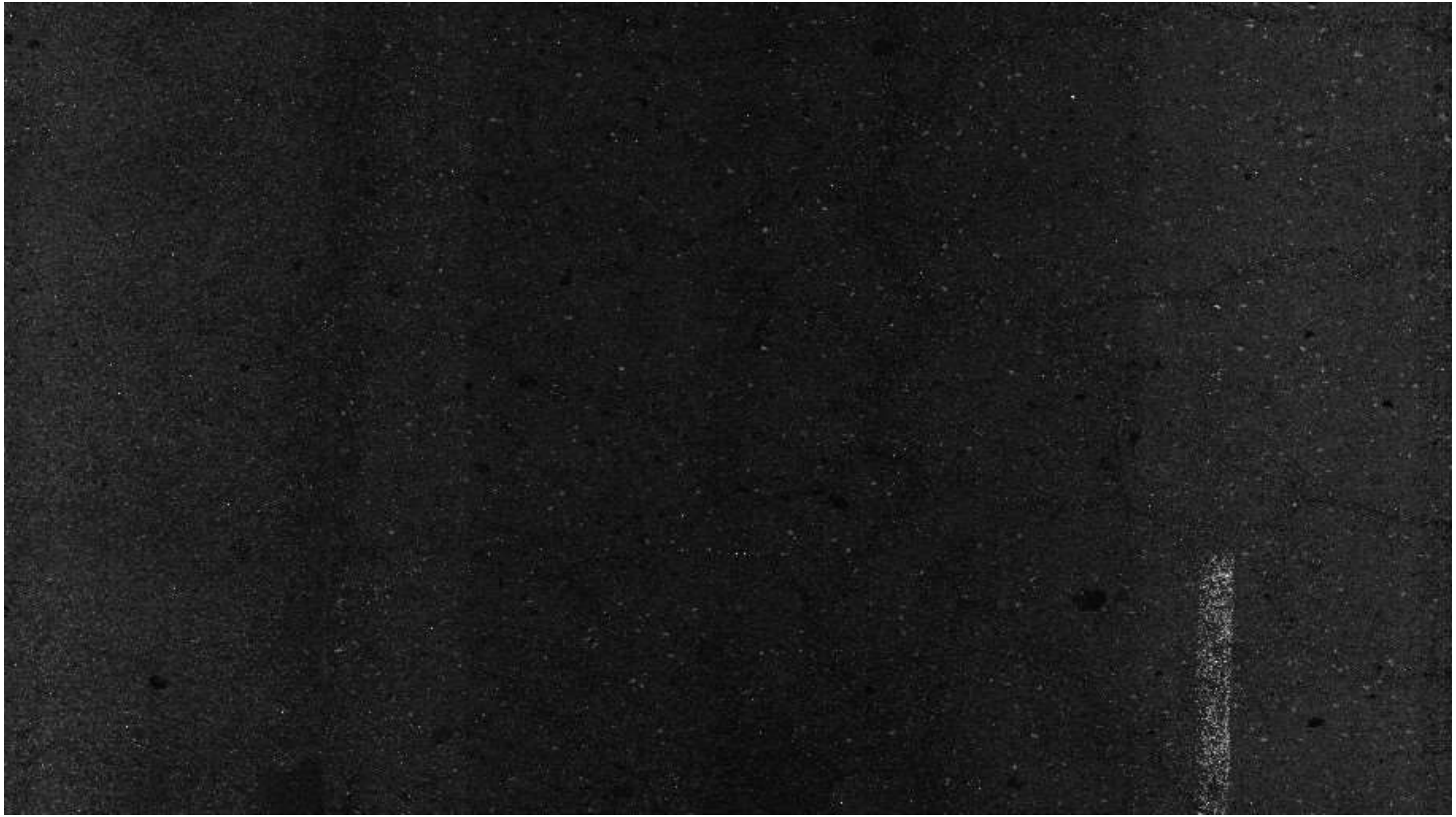
Example 1 – Depth Image



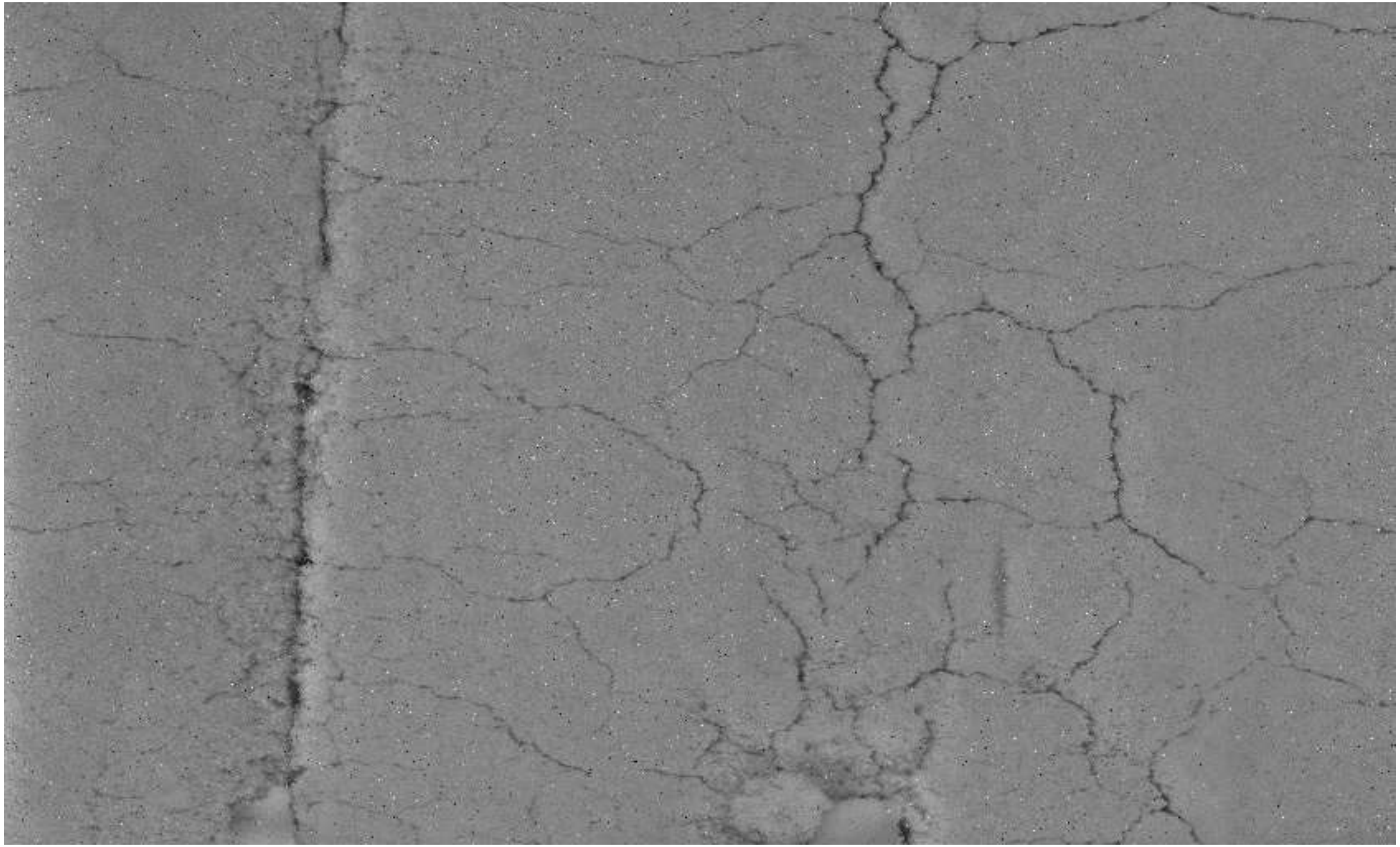
Example 1 – Crack Detection



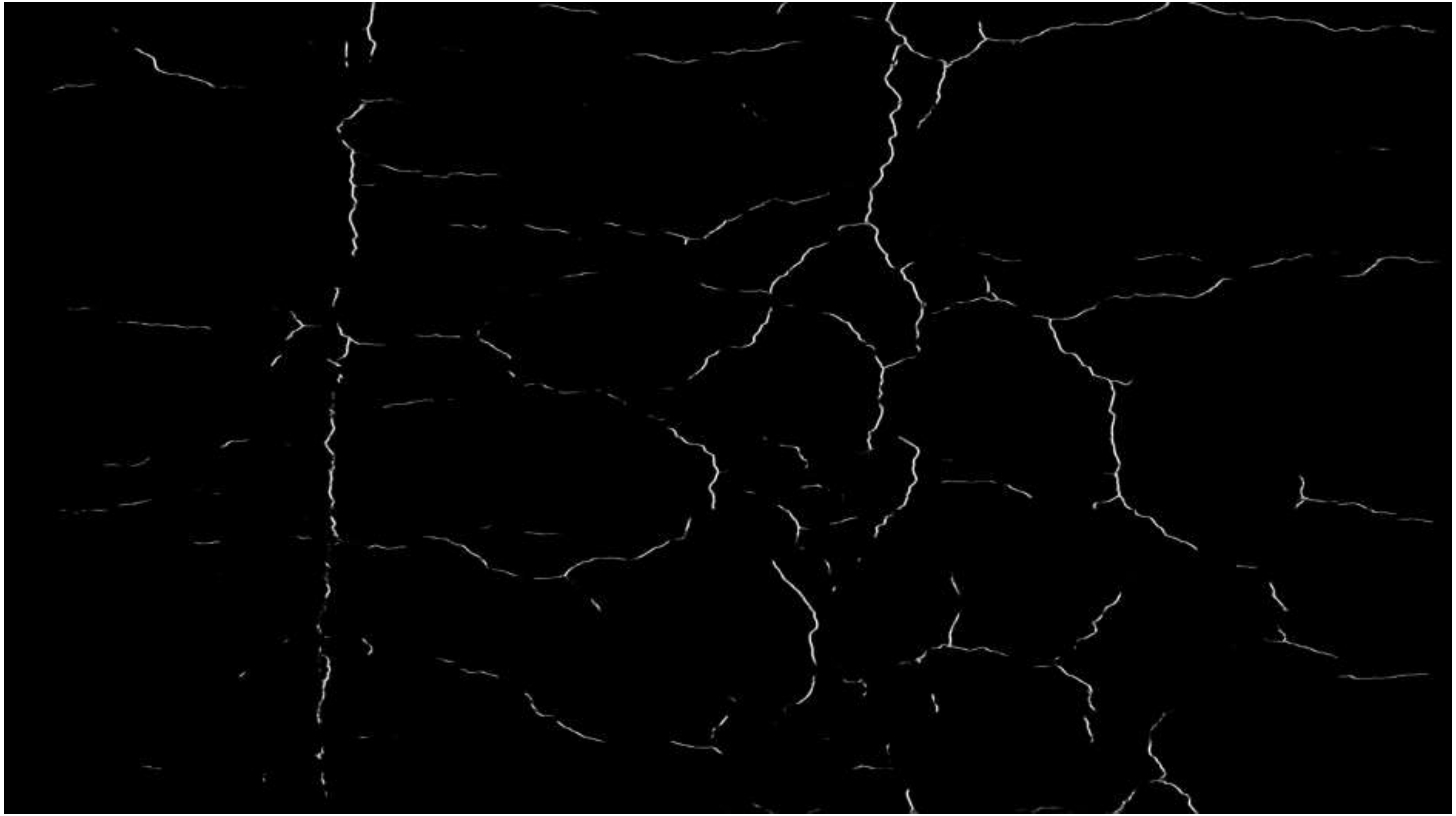
Example 2 – Real Image



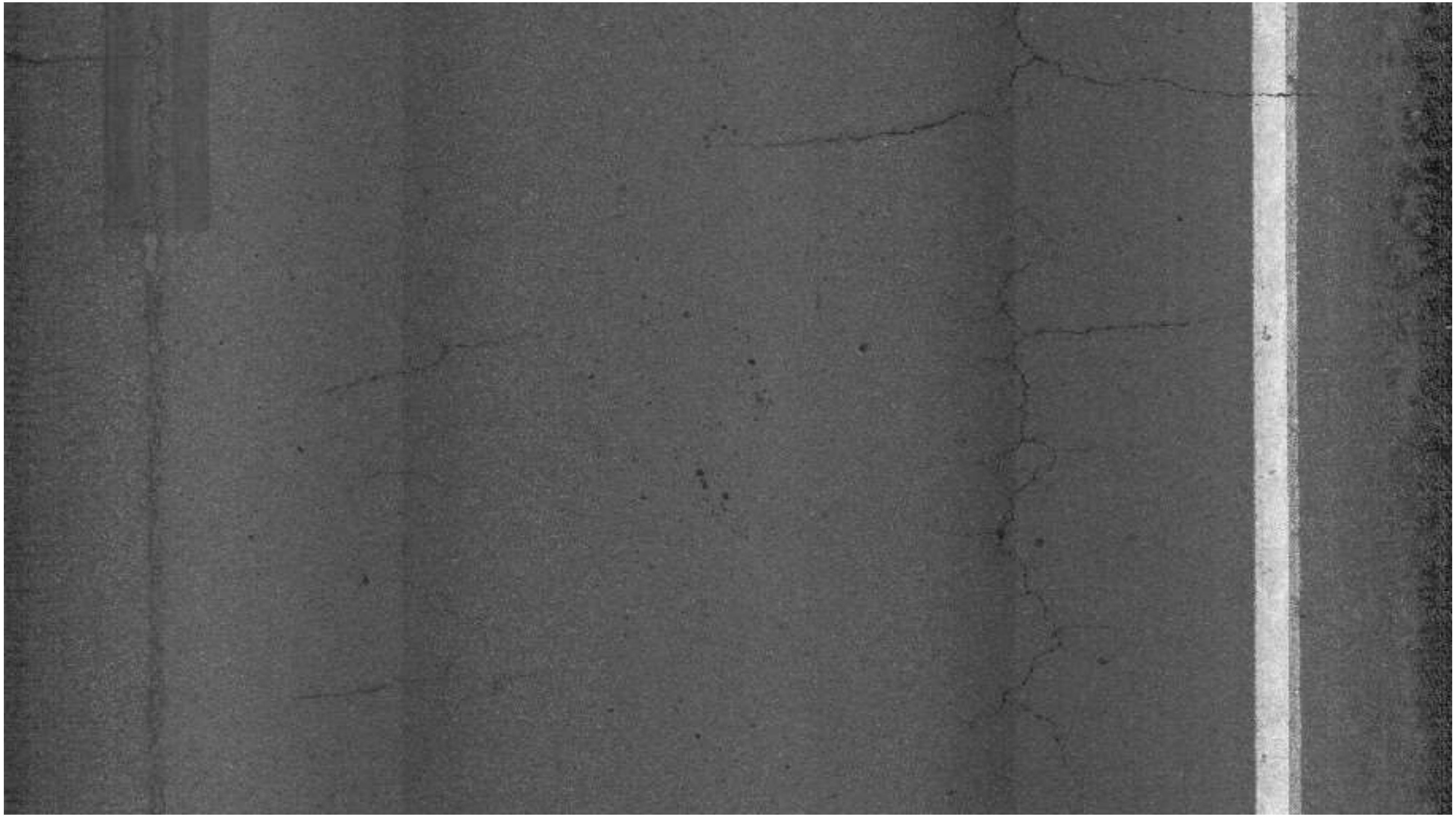
Example 2 – Depth Image



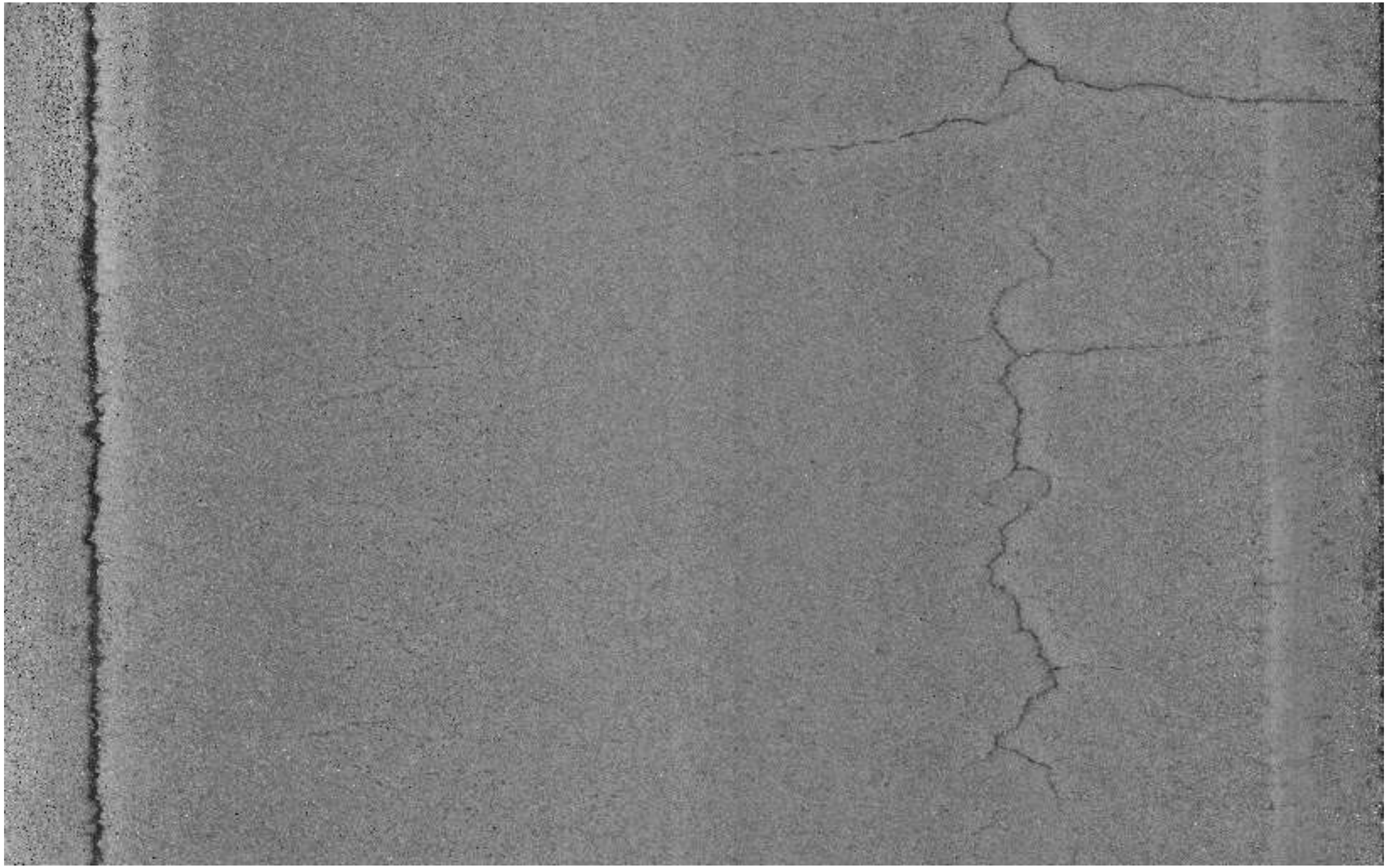
Example 2 – Crack Detection



Example 3 – Real Image

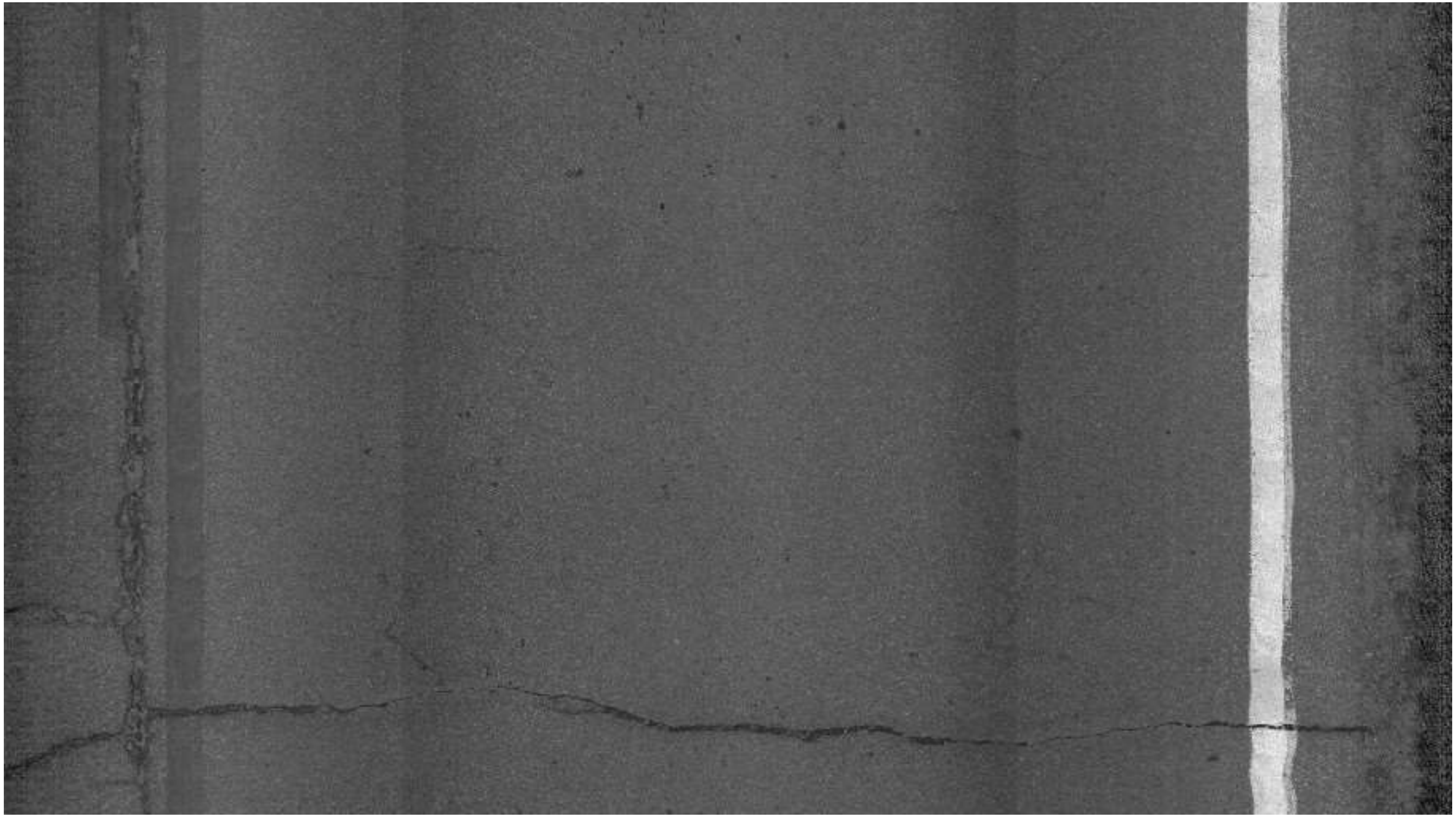


Example 3 – Depth Image

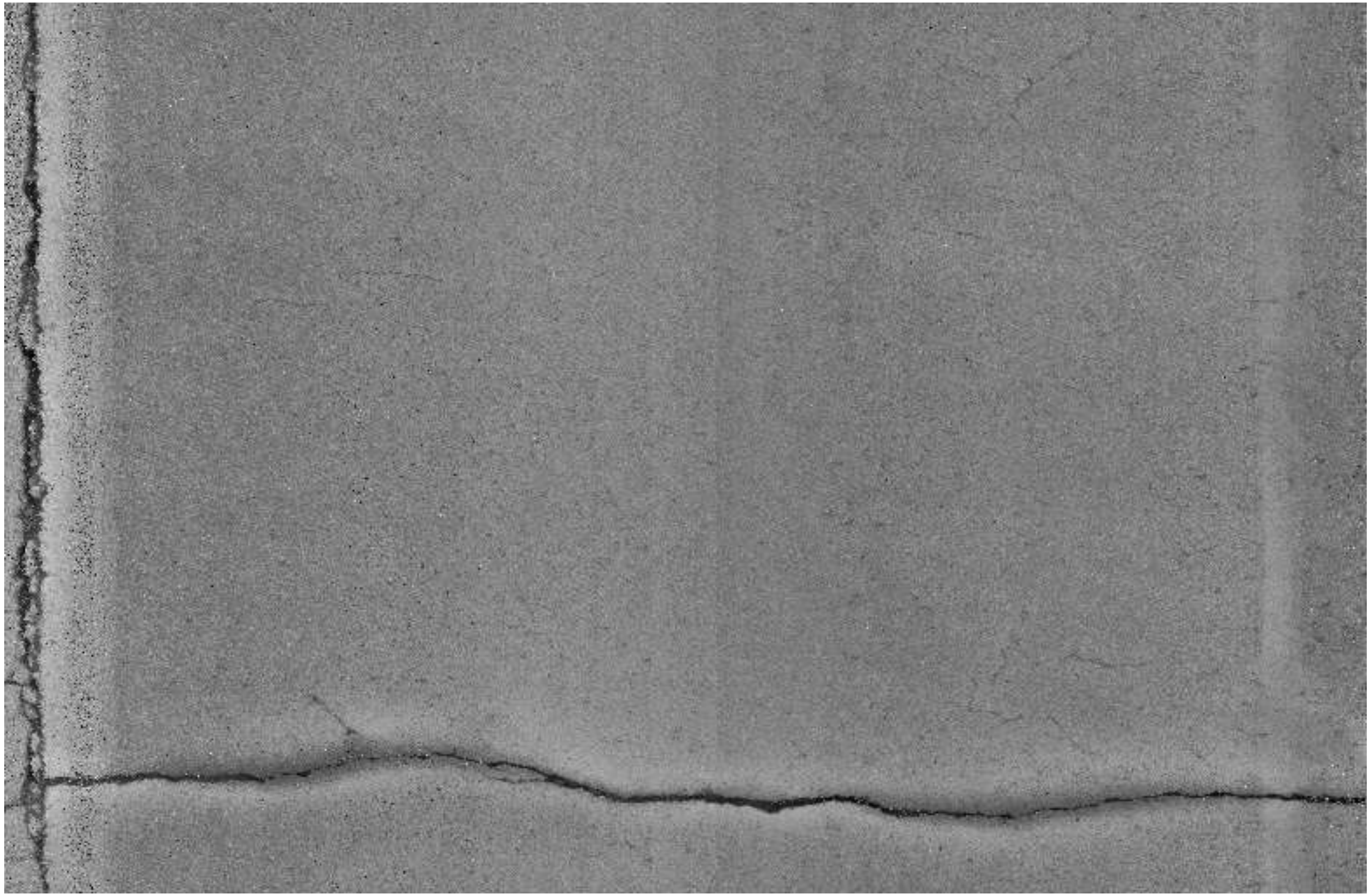


Example 3 – Crack Detection

Example 4 – Real Image

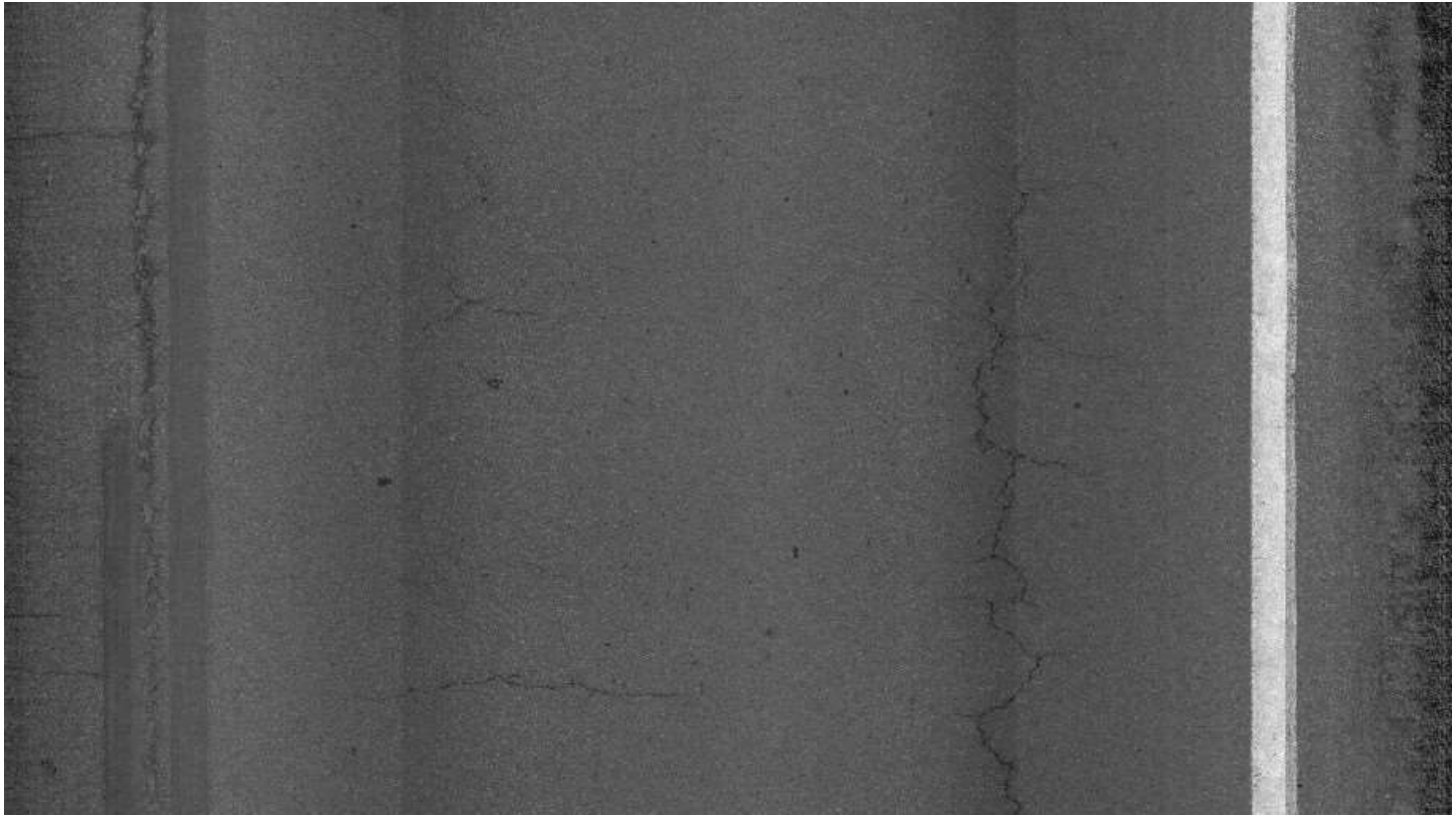


Example 4 – Depth Image

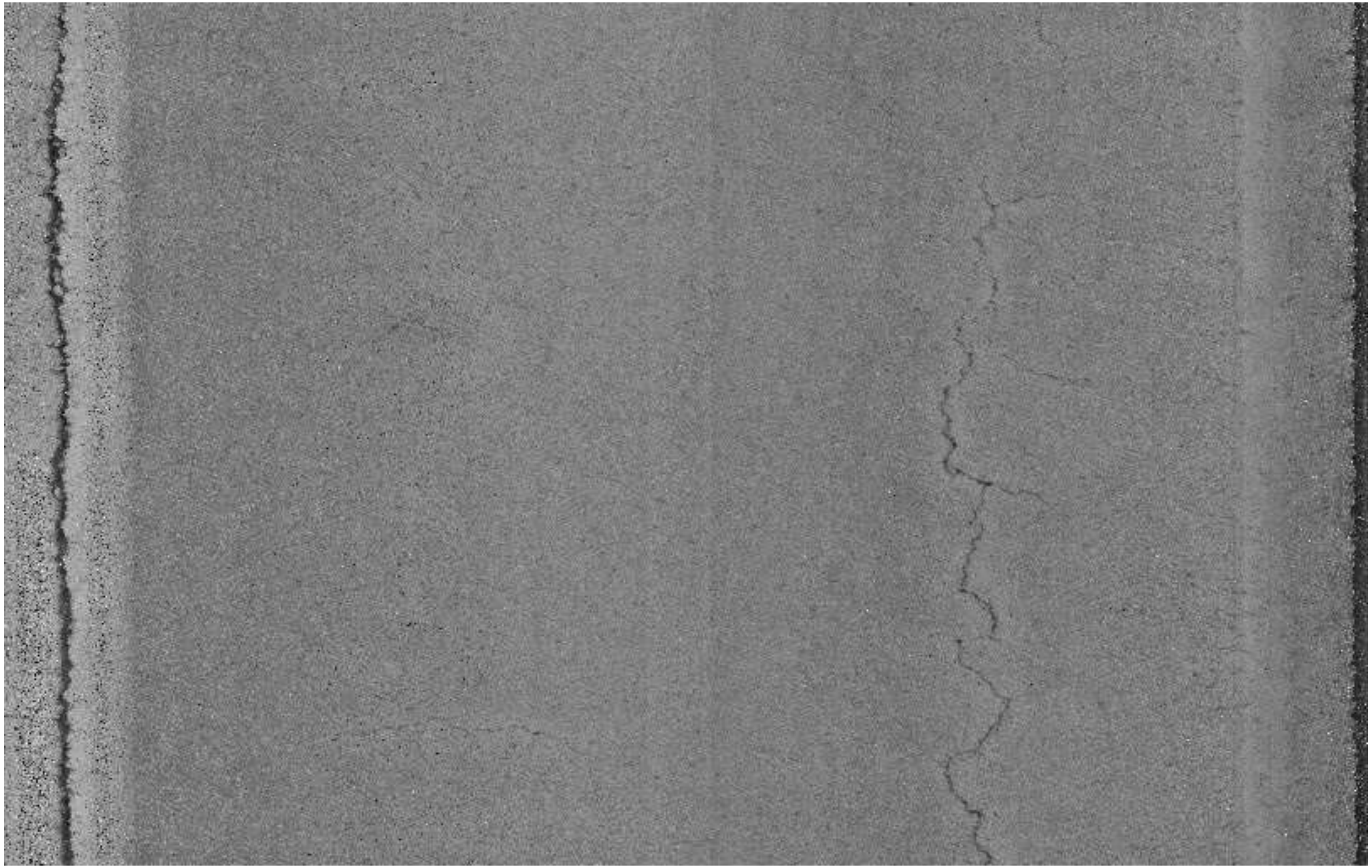


Example 4 – Crack Detection

Example 5 – Real Image

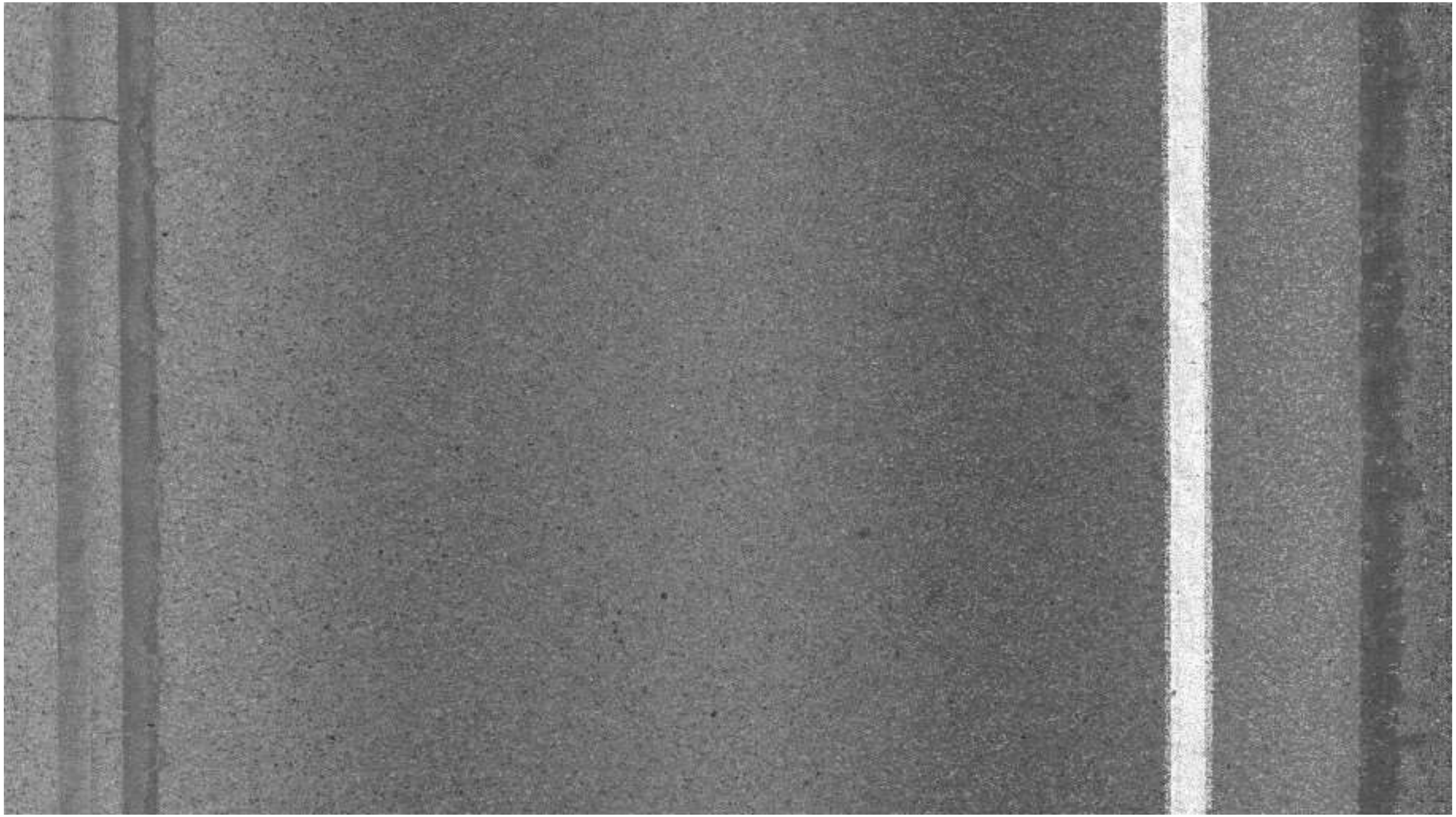


Example 5 – Depth Image

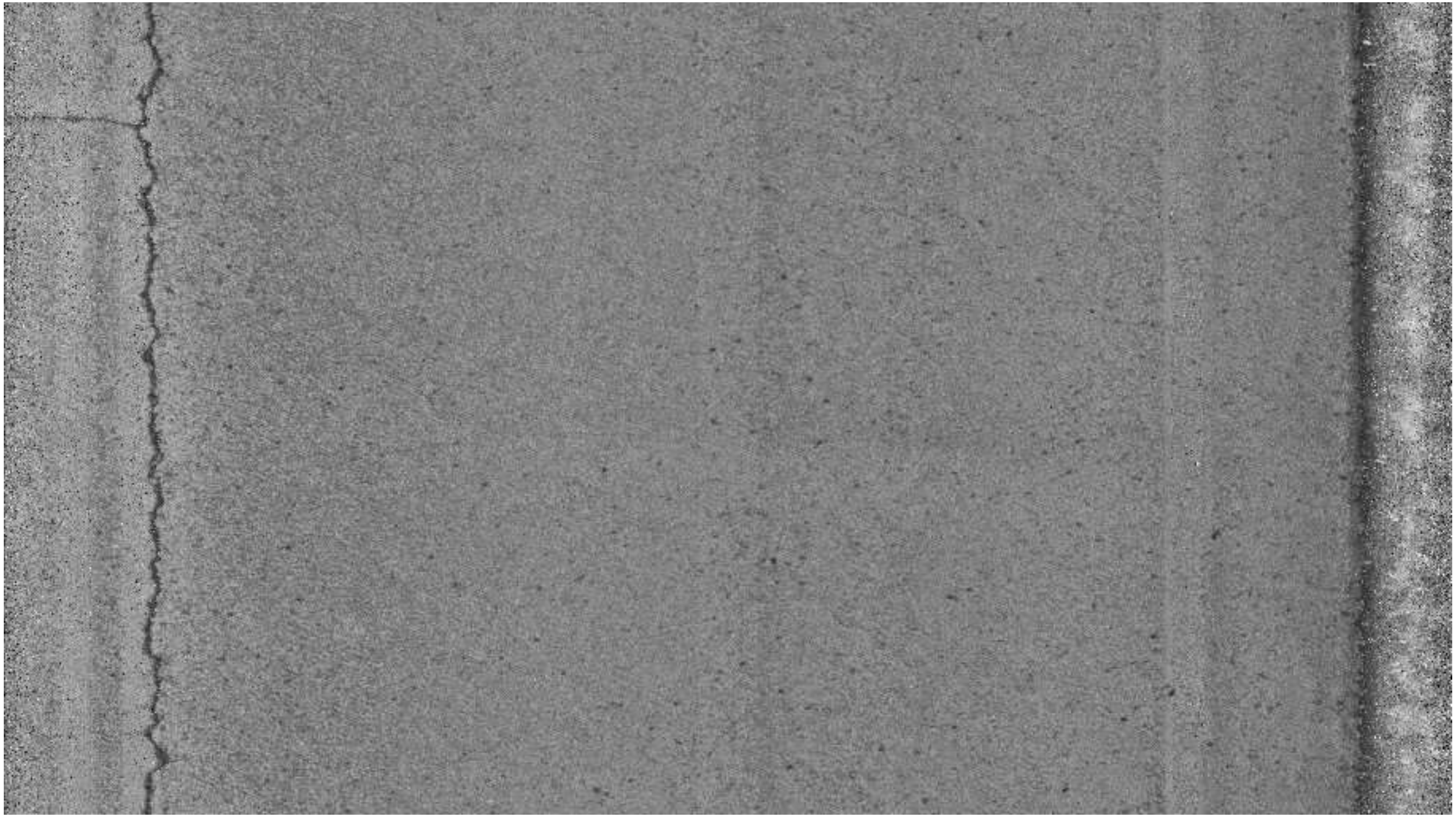


Example 5 – Crack Detection

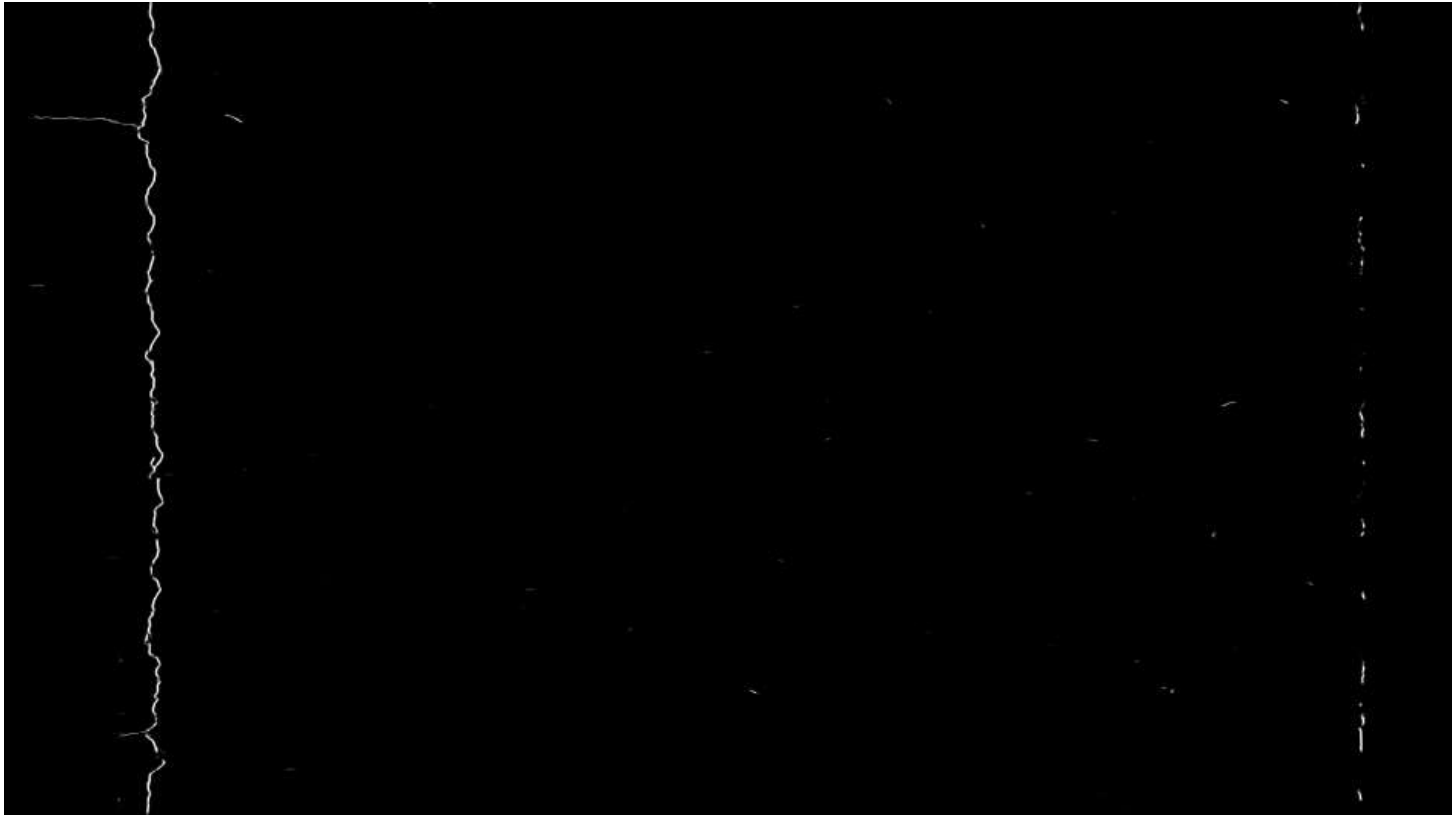
Example 6 – Real Image



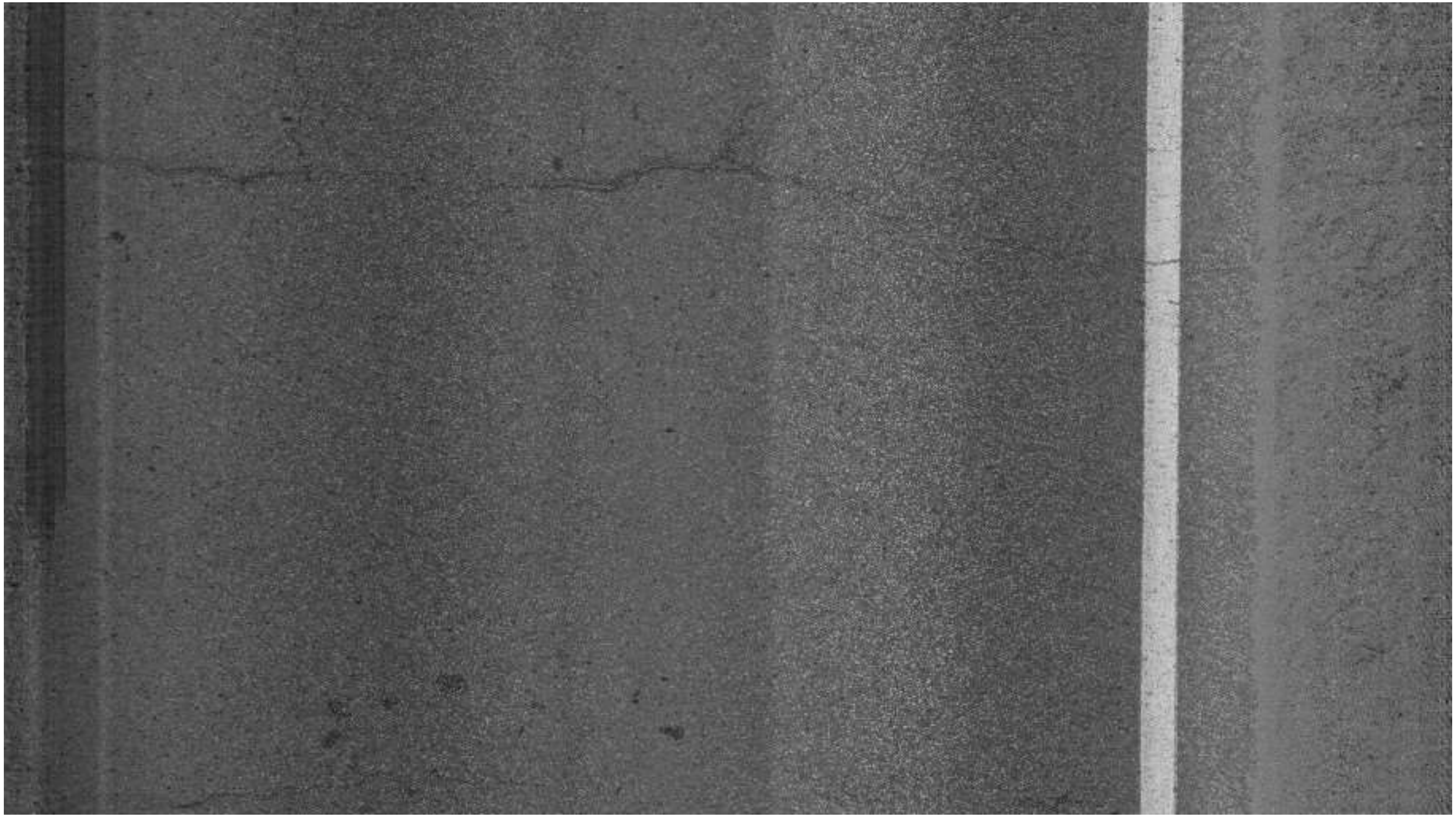
Example 6 – Depth Image



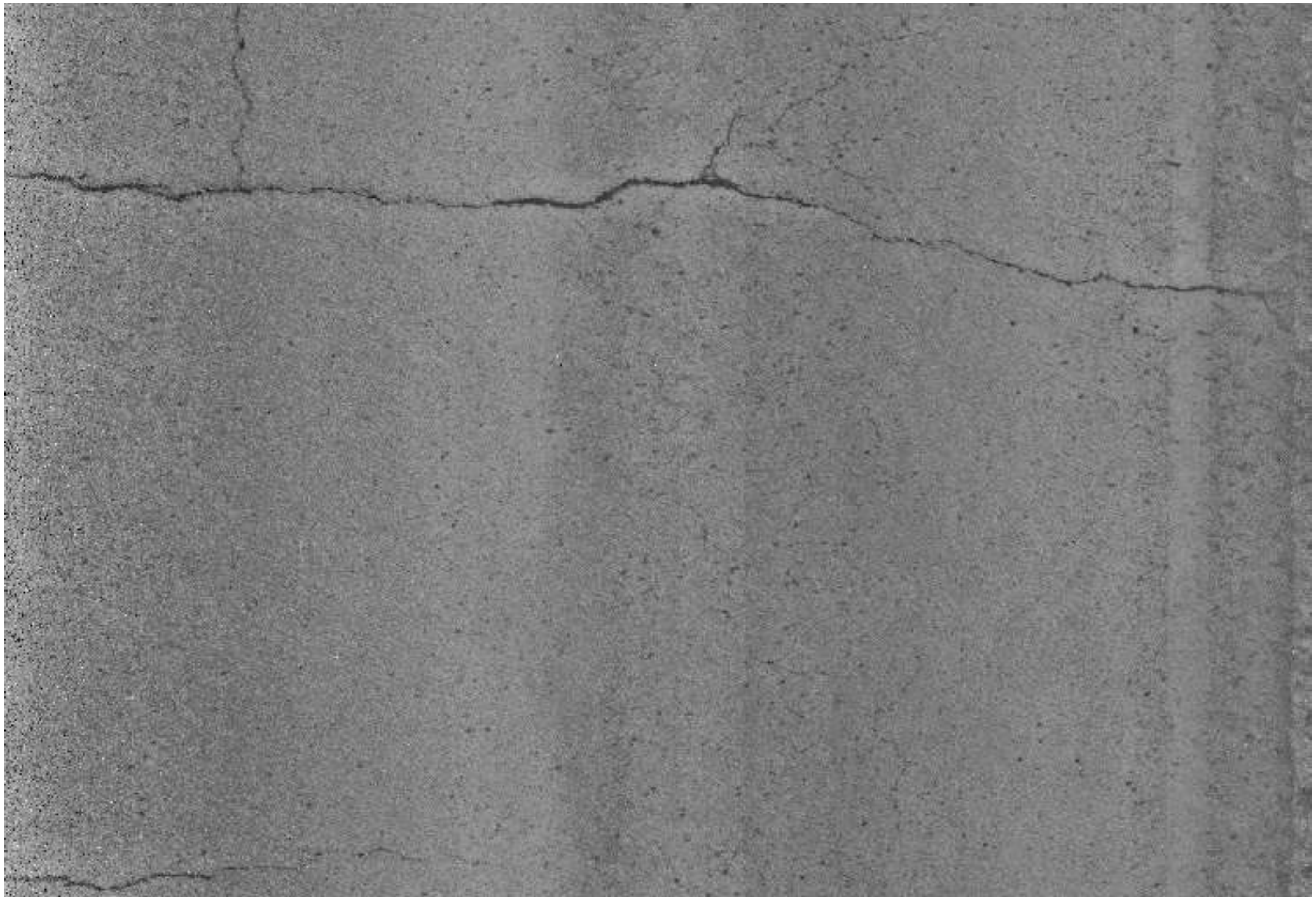
Example 6 – Crack Detection



Example 7 – Real Image



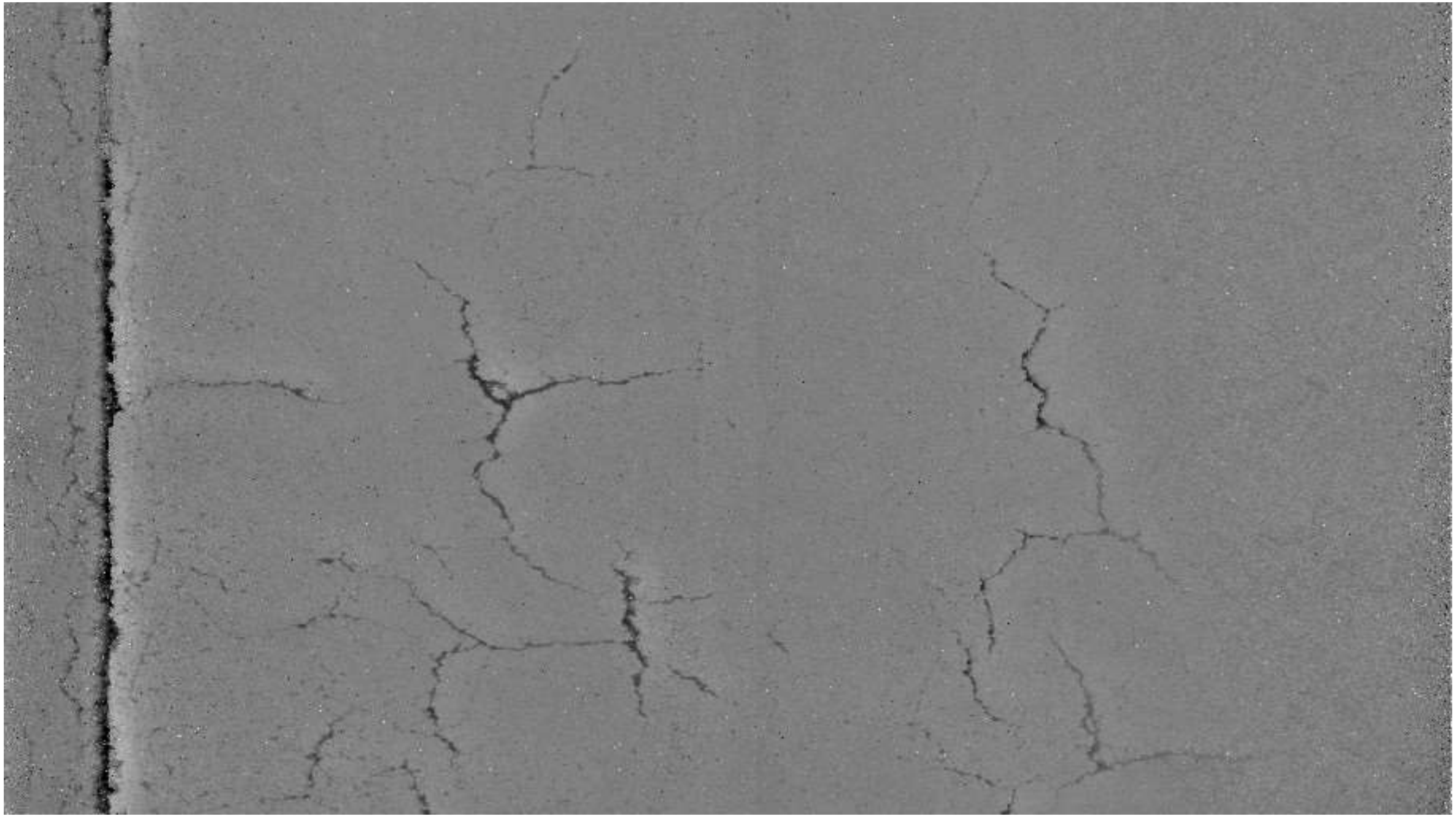
Example 7 – Depth Image



Example 7 – Crack Detection

Example 8 – Real Image

Example 8 – Depth Image



Example 8 – Crack Detection

Conclusion

- **Deep Learning** - Well suited for pavement distress detection

- **WiseCrax with UNet** – Very promising results
  - Precision = 90.9%
  - Recall = 99.9%
  - F1 Score = 94.8%
  - Continuing to learn rapidly

- **Large data sets** improve results

- **Data Augmentation**
  - Reduces burden of annotation
  - Increases speed of improvement

Thank you

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