U.S. Department of Transportation
Federal Highway Administration
Turner-Fairbank Highway Research Center

Pavement Condition and Safety Detection Project:
Utilizing AI/ML Approaches

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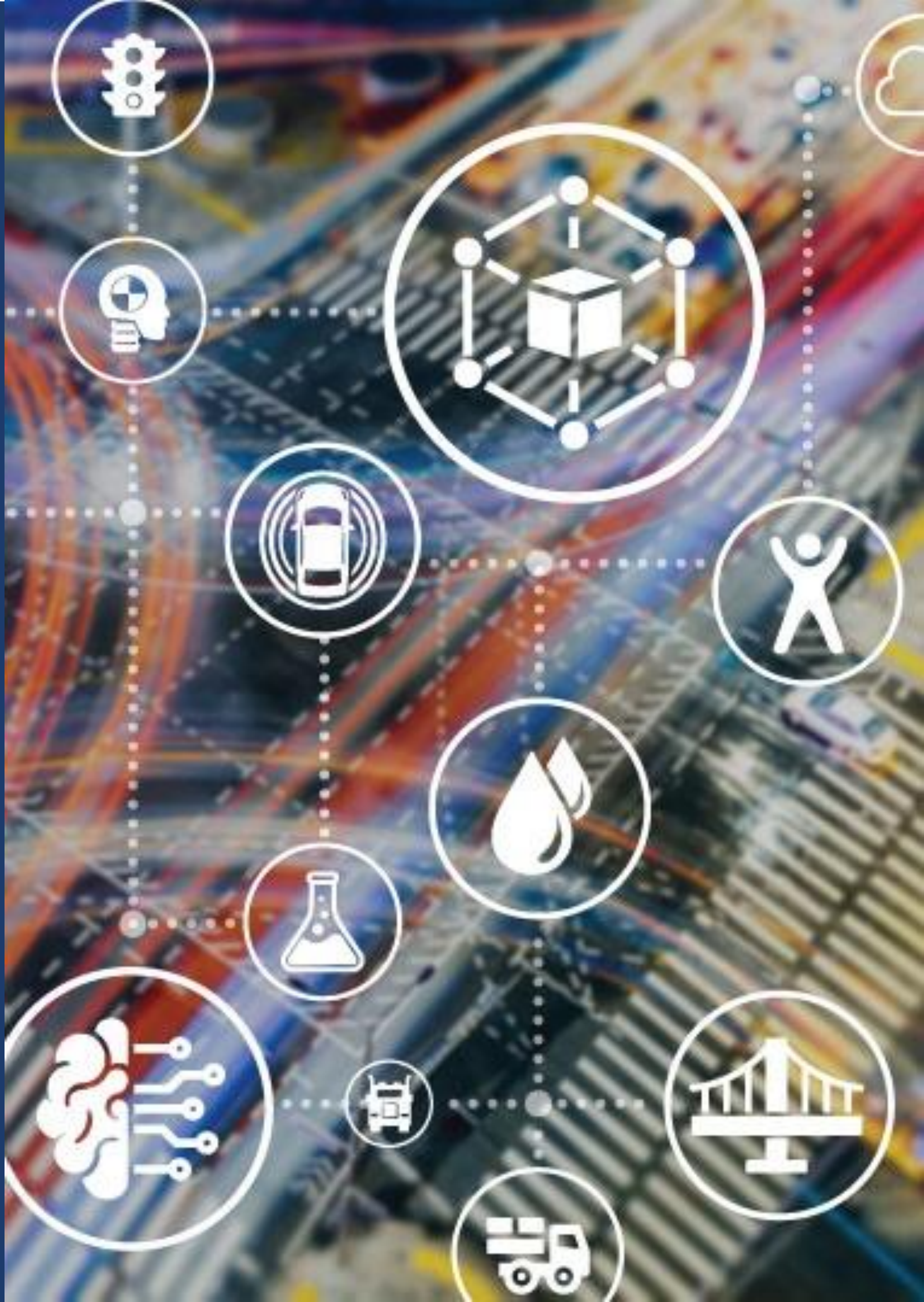

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List of Abbreviations and Acronyms (1/4)

2D	two-dimensional
3D	three-dimensional
AC	asphalt concrete
AdamW	Adam with decoupled weight decay optimizer model
AI	artificial intelligence
BPT	The British Pendulum Tester
CBAM	Convolutional Block Attention Module
CD	cross dimension
CMFs	crash modification factors
CPFM	continuous pavement friction measurement
CRS	condition rating system
CSTI	Center for Sustainable Transportation Infrastructure

List of Abbreviations and Acronyms (2/4)

DFT	Dynamic Friction Tester
DGAC	dense-graded asphalt concrete
DL	deep learning
FGM	fractal generative model
FWHA	Federal Highway Administration
GAN	generative adversarial network
GPS	Global Positioning System
HD	height dimension
HFST	high friction surface treatment
HMA	hot mix asphalt
HR	high resolution
IMU	inertial measurement unit

List of Abbreviations and Acronyms (3/4)

IoU	intersection over union.
IRI	International Roughness Index
LoRA	low-rank adaptation
LR	low resolution
ML	machine learning
MPD	mean profile depth
NCAT	National Center for Asphalt Technology
ODOT	Ohio Department of Transportation
OEM	original equipment manufacturer
OSU	Oklahoma State University
PCC	portland cement concrete
PFM	pavement friction management

List of Abbreviations and Acronyms (4/4)

PMS	pavement management system
PSC	proven safety countermeasures
RPUG	Road Profile Users' Group
RSME	root mean square error
SD	scanning dimension
SMA	Stone matrix asphalt
SCRIM	Sideway-force Coefficient Routine Investigation Machine
SPF	safety performance
SR	super resolution
SRI	Safer Roads Index
VAE	variational autoencoder
VTTI	Virginia Tech Transportation Institute

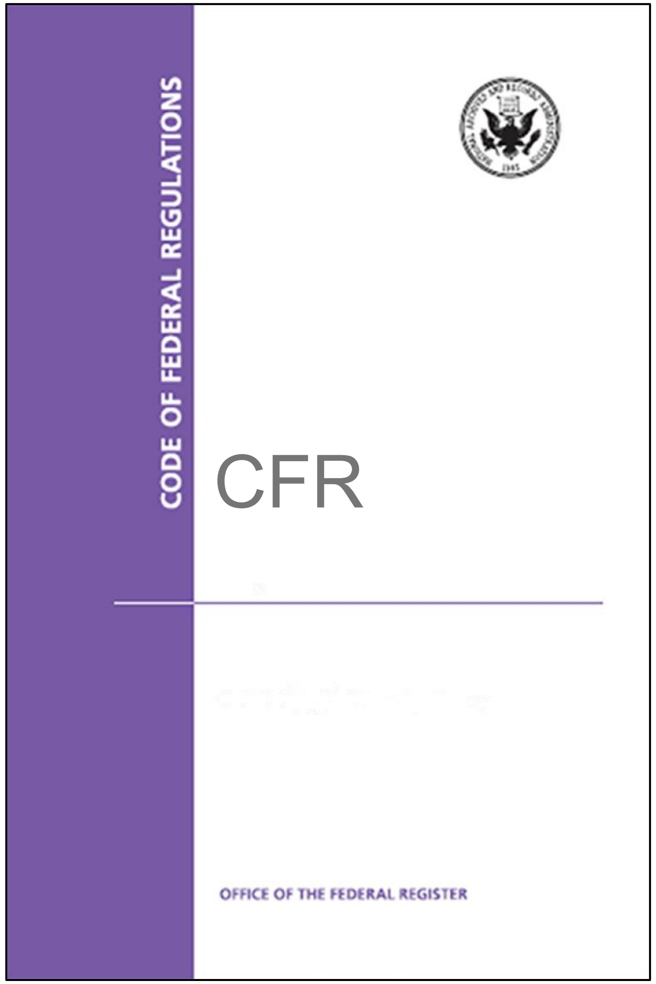
Overview of Pavement Friction and Safety

U.S. Department of Transportation
Federal Highway Administration
Turner-Fairbank
Highway Research Center

23 CFR Part 626

§626.3 Pavement Design Policy

Pavement shall be designed to accommodate current and predicted traffic needs in a ***safe***, durable, and cost-effective manner.



Source: U.S. Government Printing Office.[(1)]

Scale of the Road Safety Challenge

The crisis on our roadways *remains urgent* based on estimated roadways fatalities:(2)

Estimates of Motor Vehicle Traffic Fatalities, 2021-2023			
2021 Estimates*	2022 Estimates	2023 Estimates	Percent Decrease from 2022 to 2023
43,230	42,514	40,990	**-3.6%**

**2021 was the largest number of roadway fatalities since 2005.*

The Safety Paradigm

The Safe System Approach: 6 Core Principles

- Death/Serious Injury is Unacceptable
- Humans Make Mistakes
- Humans are Vulnerable
- Responsibility is Shared
- Safety is Proactive
- Redundancy is Crucial

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Federal Highway Administration

Source: FHWA.

Introduction of Pavement Condition and Safety Detection

U.S. Department of Transportation
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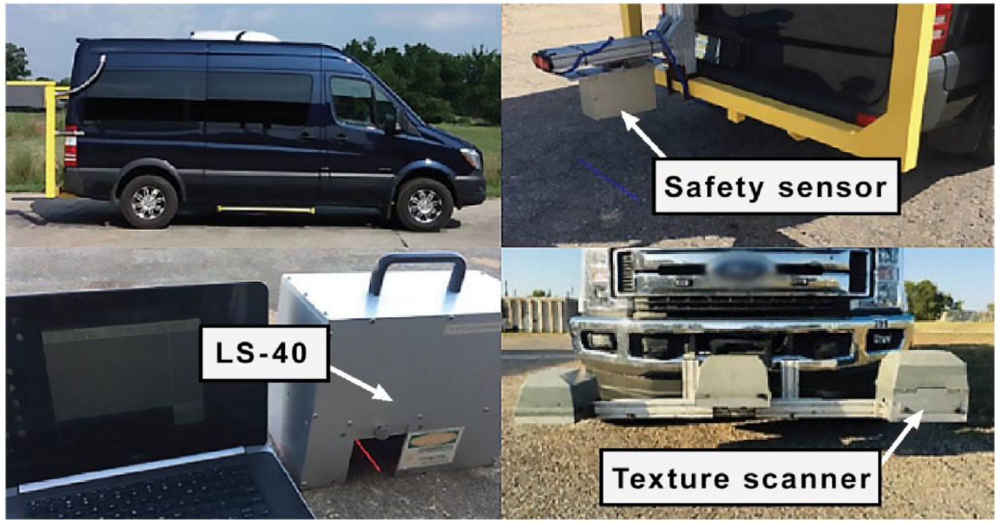
Explanatory Advanced Research Project: Artificial Intelligence Approaches to Multi-Object Evaluation of Pavement Condition and Safety

- The research team is developing new AI approaches, using DL methods, to better monitor pavement conditions for safety.
- The research team is using four pavement condition and texture data collection instruments.
- The goals are developing a software interface to display 3D virtual pavement surfaces and submillimeter-resolution 3D texture images and calculating the proposed texture parameters, estimating friction numbers, and evaluating safety via the developed DL models.



All images source: FHWA.[8]

1. Surface Condition Detection

Introduction

- Excluding drivers' own reasons, pavement condition causes about **50 percent** of traffic accidents annually.[9]
- Poor pavement conditions cause economic losses of **$6.8 billion** annually.[9]
- Poor road conditions increase commuting costs by **$130 billion** annually.[10]

Detection Classes

- Distress detection objects include **crack** and **pothole.**
- Nondistress detection objects include **patch**, **sealed crack**, **manhole**, **lane marking**, and **expansion joint.**


Crack


Pothole


Patch


Sealed crack

All images source: FHWA.

Challenges

Traditional inspection is **time-consuming and labor-intensive**.


Manual and semiautomated detection

Existing DL models face several challenges:

1. Most focus on single classes and single modalities, making **acquiring comprehensive and rich information difficult**.
2. Multiclass detections often suffer from an **imbalance** in the number of training sample classes.

2. Safety Evaluation

Introduction

- Inadequate pavement conditions: contribute to approximately 30 percent of the annual traffic accidents.(11)
- Insufficient pavement **friction**: often a determining factor for a crash, especially under wet conditions.




Contact- and Water-Based Friction Devices

- Limited measurement repeatability.
- Only cover a small portion of the roadway.


BPT (OSU)


DFT (OSU)


Grip Tester (OSU)

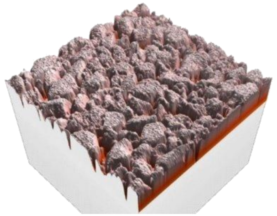

Locked-Wheel Skid Trailer (ODOT)

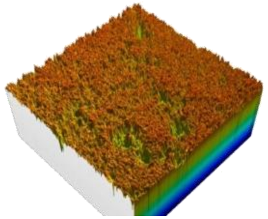

SCRIM (FHWA)

Pavement Texture

Pavement texture: crucial for tire-pavement friction:

- **Macrotexture (wavelengths: 0.5 ~ 50 mm):** allows water drainage, reduces hydroplaning risk, enhances friction at higher speeds, and it can be measured at highway speed.
- **Microtexture (wavelengths: <0.5 mm):** affects tire rubber deformation and low-speed friction, and it can only be measured at a static or low speed.


Macrotexture


Microtexture

All images source: FHWA.

Pavement Safety Prediction With Generative Super-Resolution Microtexture Reconstruction

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3.1. Research Objectives

01

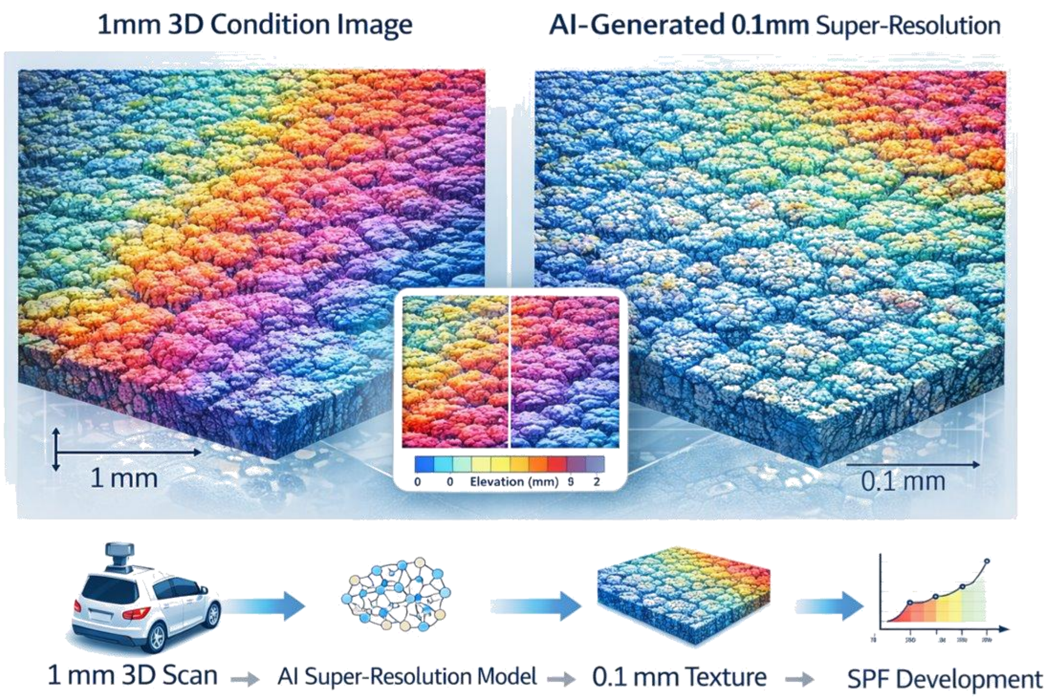
Texture data acquisition and validation:

Validate data consistency and quality of **3D submillimeter condition and 0.1-mm texture data** acquired on selected pavement sections. Develop AI algorithms for generative super-resolution (0.1mm) microtexture data for **noncontact friction safety evaluation.**

02

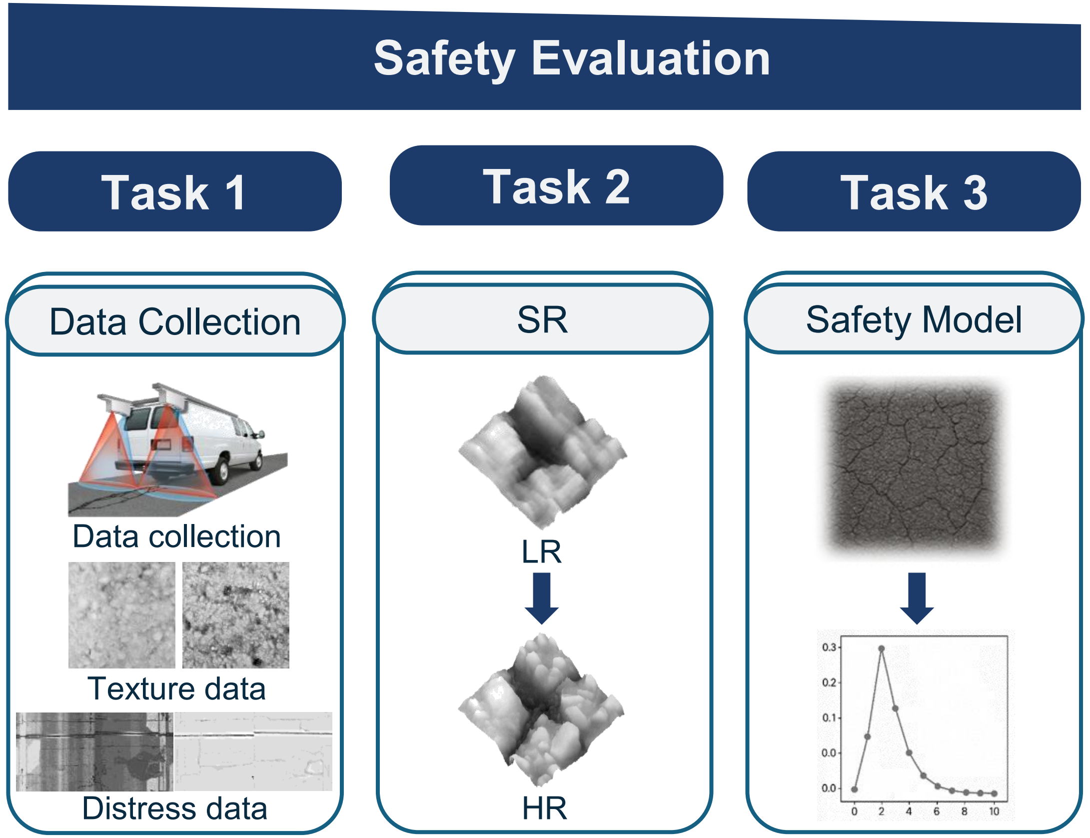
Noncontact friction safety evaluation:

Develop safety performance functions based on 0.1 mm 3D images for **noncontact friction safety evaluation.**



All images source: FHWA.

3.2. Research Tasks



All images source: FHWA.

- Field data collection: acquire macro- and microtexture data.
- Super-resolution reconstruction based on GAN, Diffusion models, Flow matching, and FGMs. The best model is confirmed for safety model development.
- Safety model based on Poisson model, Negative Binomial, Heterogeneous Negative Binomial, Conway-Maxwell-Poisson, and Heterogeneous Conway-Maxwell-Poisson used.

Task 1: Field Data Collection and Validation of 0.1-mm 3D Imaging System: Collection Device

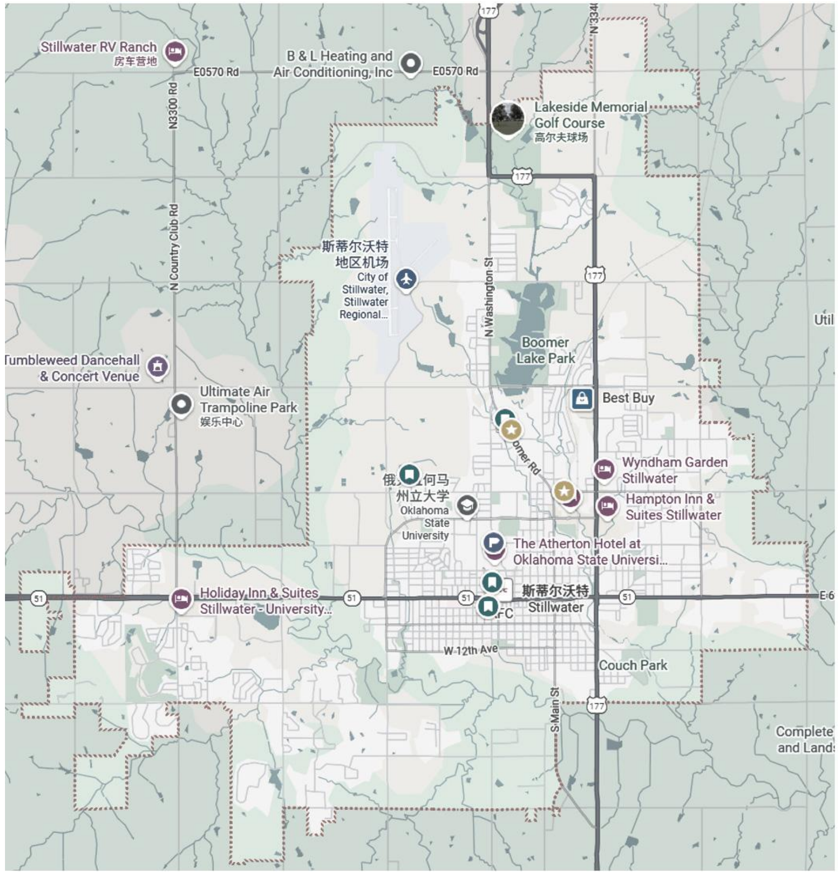
- **Consistent 0.1-mm transverse resolution.**
- **Varied longitudinal resolution.**

0.1-mm Safety Sensor

Source: FHWA.

Collection Speed	Longitudinal Resolution
1.5 mph	0.1 mm
3 mph	0.2 mm
6 mph	0.4 mm
12 mph	0.8 mm
24 mph	1.6 mm
48 mph	3.2 mm
96 mph	6.4 mm

Task 1: Field Data Collection and Validation of 0.1-mm 3D Imaging System: Collection Sites



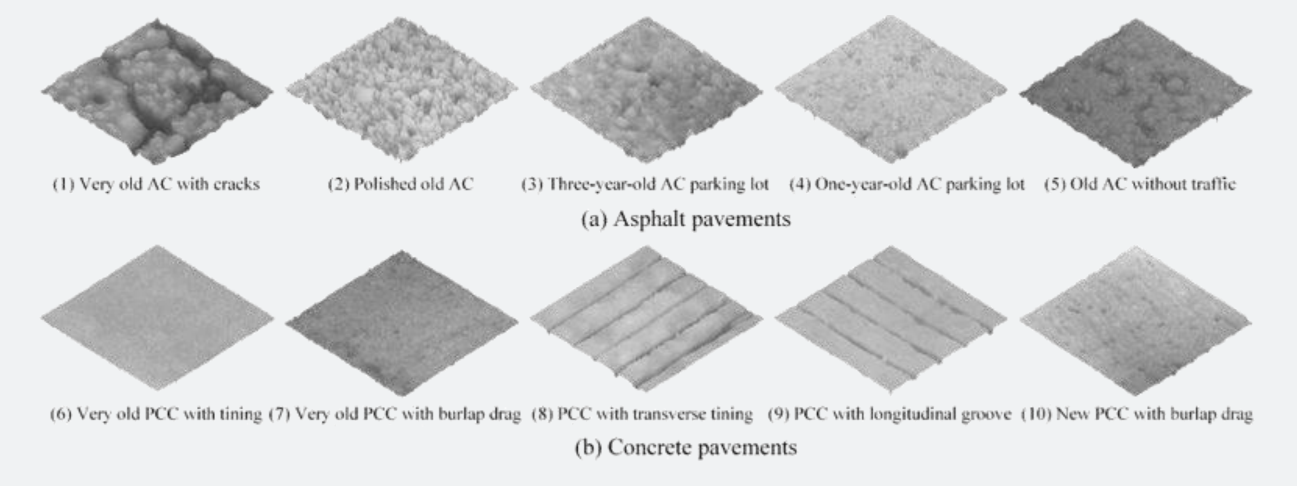
© 2026. Google® Street View™. Modified by FHWA to enhance color contrast.[12]

10 pavement sites collected in Stillwater, OK: 5 AC pavements and 5 PCC pavements:

- Collect true 0.1-mm texture data at a speed < 1.5 mph via the 0.1-mm 3D safety sensor.
- Collect 9,280, 800, and 1,600 images with dimensions of 512 × 4,096 pixels for model training, validation, and testing, respectively.

Surface	Data Description	Surface	Data Description
AC-1	Very old AC with cracks with light traffic	PCC-1	Very old PCC with tinning with light traffic
AC-2	Polished old AC with heavy traffic	PCC-2	Very old PCC with burlap drag with light traffic
AC-3	3-yr-old AC parking lot with light traffic	PCC-3	PCC with transverse tinning with heavy traffic
AC-4	1-year-old AC parking lot with light traffic	PCC-4	PCC with longitudinal groove with heavy traffic
AC-5	Old AC without traffic	PCC-5	New PCC with burlap drag without traffic

Task 1: Field Data Collection and Validation of 0.1-mm 3D Imaging System: Data Collection



Source: FHWA.

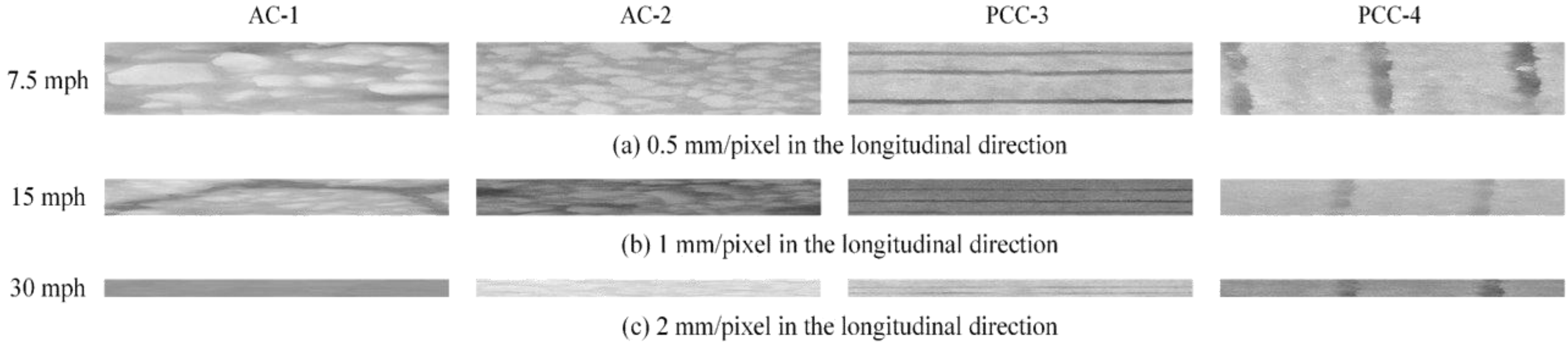
Texture data.

- **Selection of validation sites: Select sites** with various pavement conditions and surface textures.
- **Field data collection:**
  - Use 3D surface data at a 0.5-mm resolution for conditions and a 0.1-mm resolution for textures.
  - Use LS-40 HR static texture data.
  - Set the AMES® texture profiler at a 0.5 mm resolution.

Task 1: Field Data Collection and Validation of 0.1-mm 3D Imaging System: Data Sample

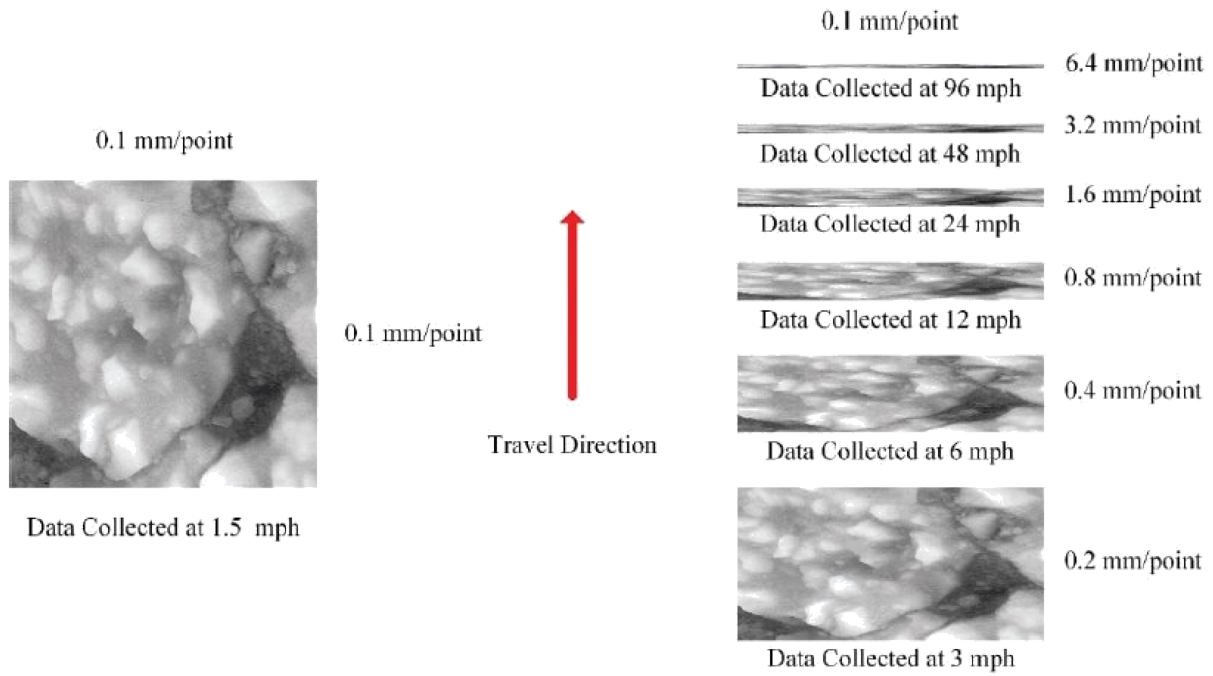
Real LR data collected via a 0.1-mm safety sensor on the same 10 pavement sites as the higher than 0.1 mm true texture images in Dataset-1 at various speeds.

- Collection speeds: 7.5 mph, 15 mph, and 30 mph.
- Resolution of image data along the longitudinal direction: 0.5 mm, 1 mm, and 2 mm.



Source: FHWA.

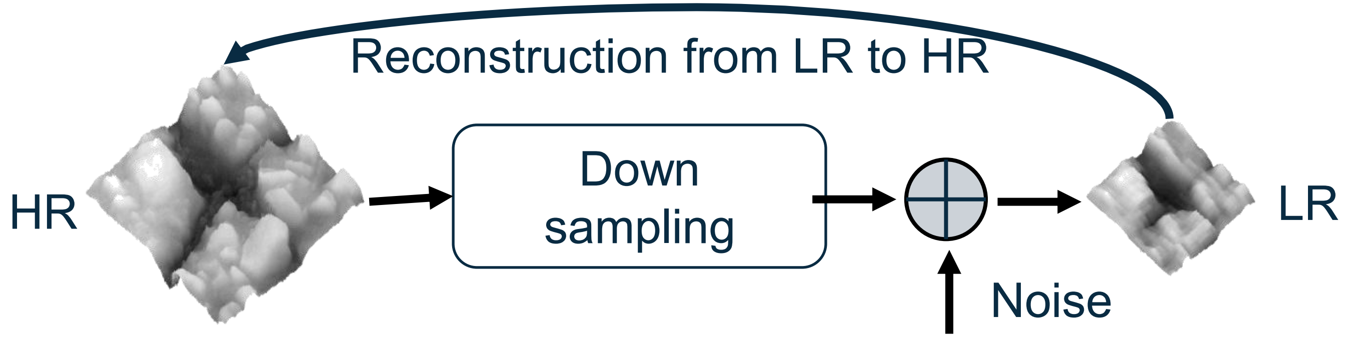
Task 2: DL for Generating SR Texture Data: Data Process



3D safety sensor:

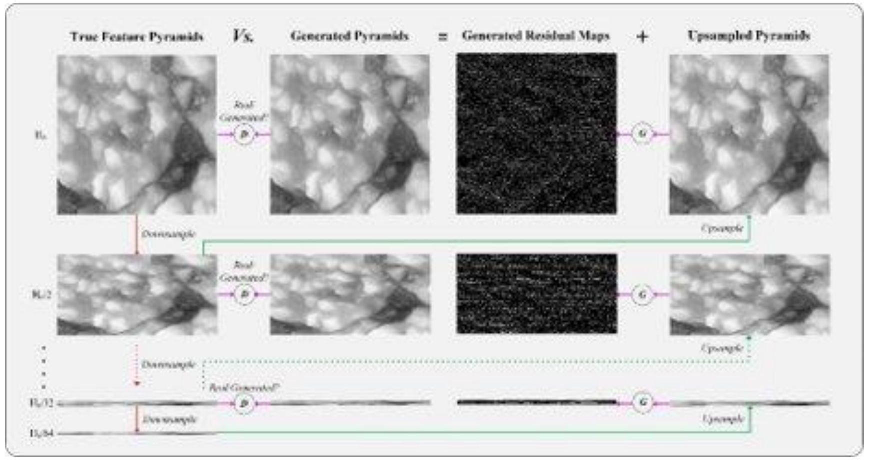
- Consistent 0.1-mm resolution along transverse direction.
- Various resolution along travel direction at higher speeds.

LR-HR pairs in down-sampling and reconstruction processes.



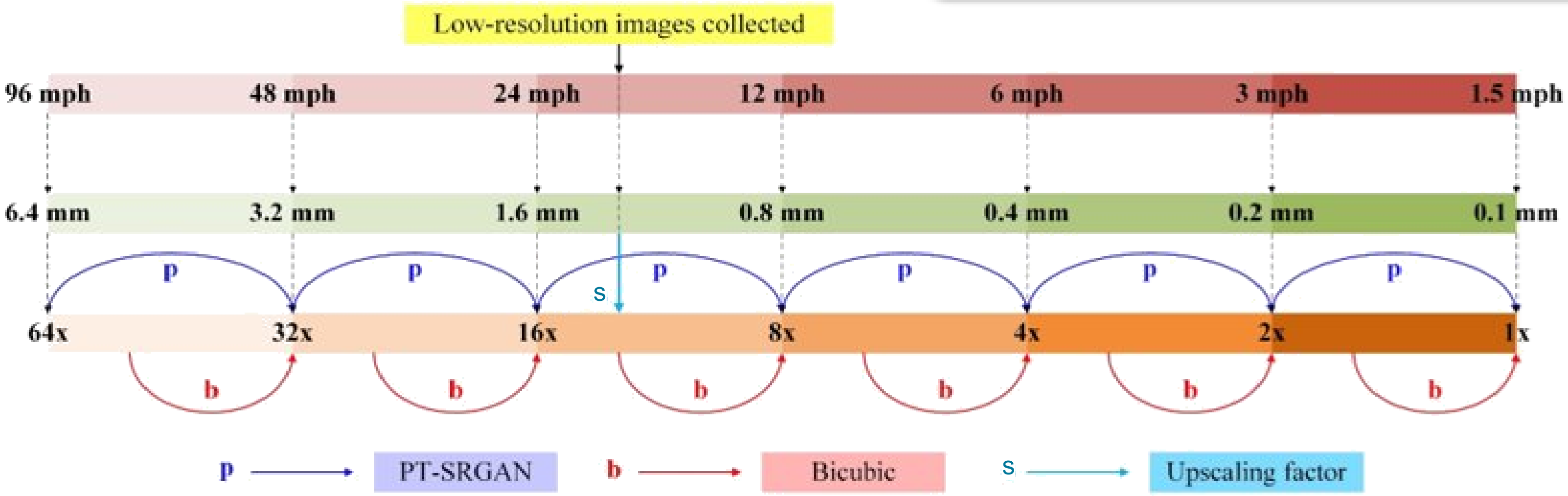
All images source: FHWA.

Task 2: DL for Generating SR Texture Data: SR Reconstruction



Pseudo-Laplacian pyramid—generates six scales of LR images and subband residuals for generative model training:

- Enables progressive construction of HR images from LR images along the travel direction only.
- Uses the nearest neighbor for interpolation during down-sampling and up-sampling processes.

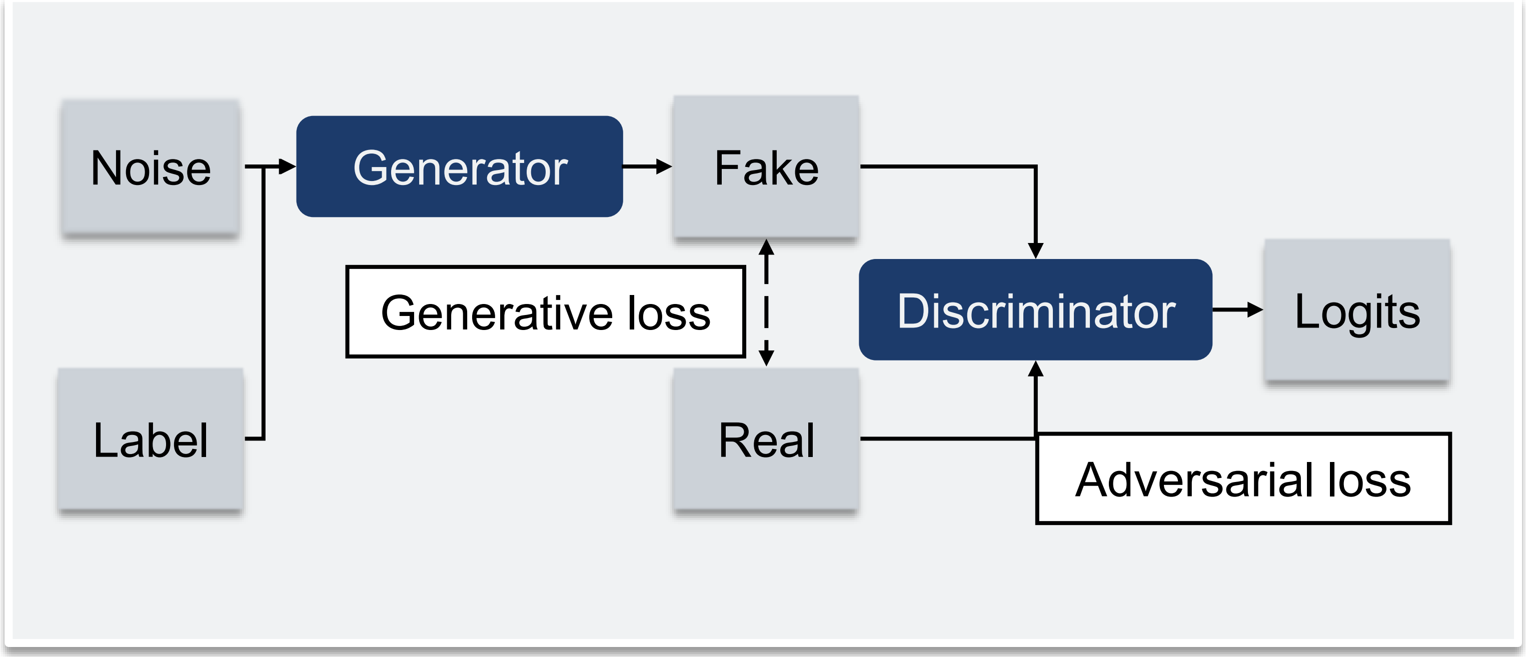


Bicubic interpolation + generative models: designed to reconstruct 0.1 mm texture data from LR images obtained at any data collection speeds (≤96 mph).

All images source: FHWA.

Task 2: DL for Generating SR Texture Data: GAN (1/2)

Introduction to GAN



Source: FHWA.

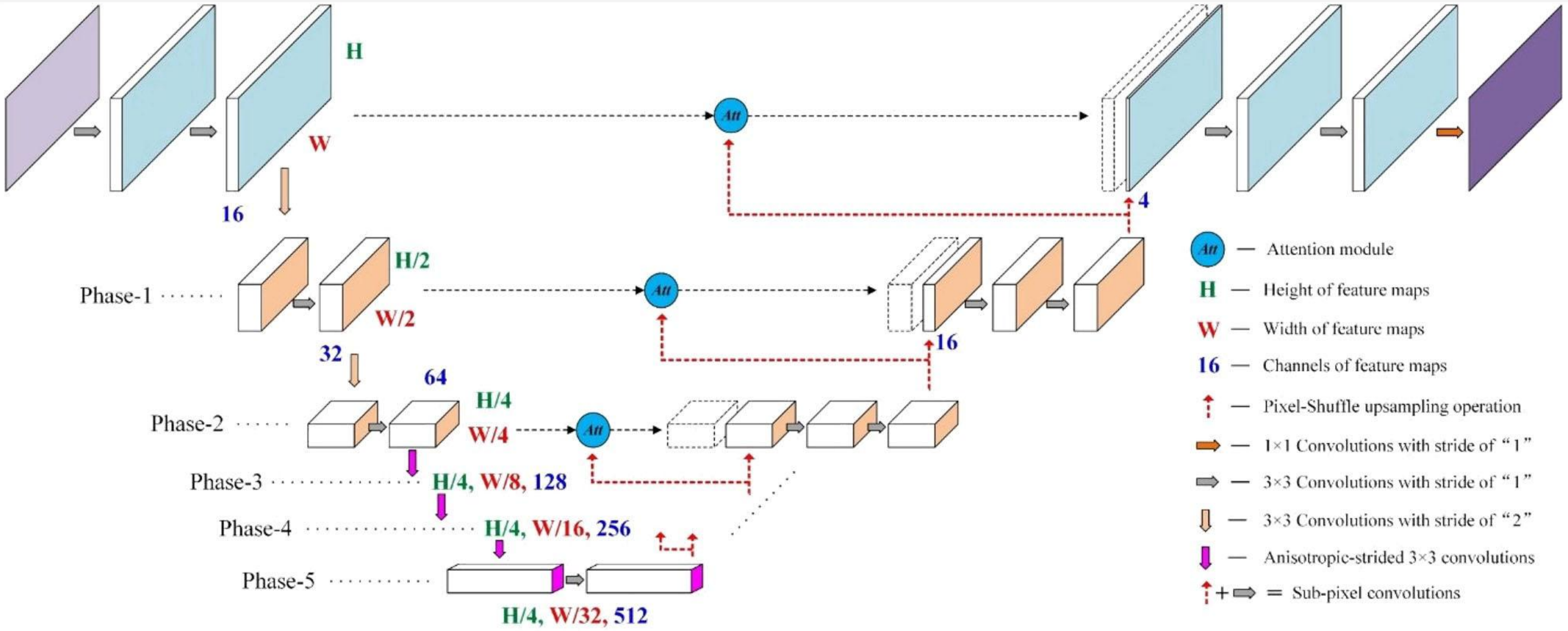
Widely used in image generation and SR reconstruction:

- **Generator:** maps random noise to a synthetic that mimics the real data distribution.
- **Discriminator:** distinguishes real samples from generated ones by outputting logits or the probability of being real.
- **Loss function:** uses generator tries to minimize the discriminator's ability to tell real from fake, while the discriminator tries to maximize this difference.

Task 2: DL for Generating SR Texture Data: GAN (2/2)

Generator of recursive SR GAN: modified attention U-Net:

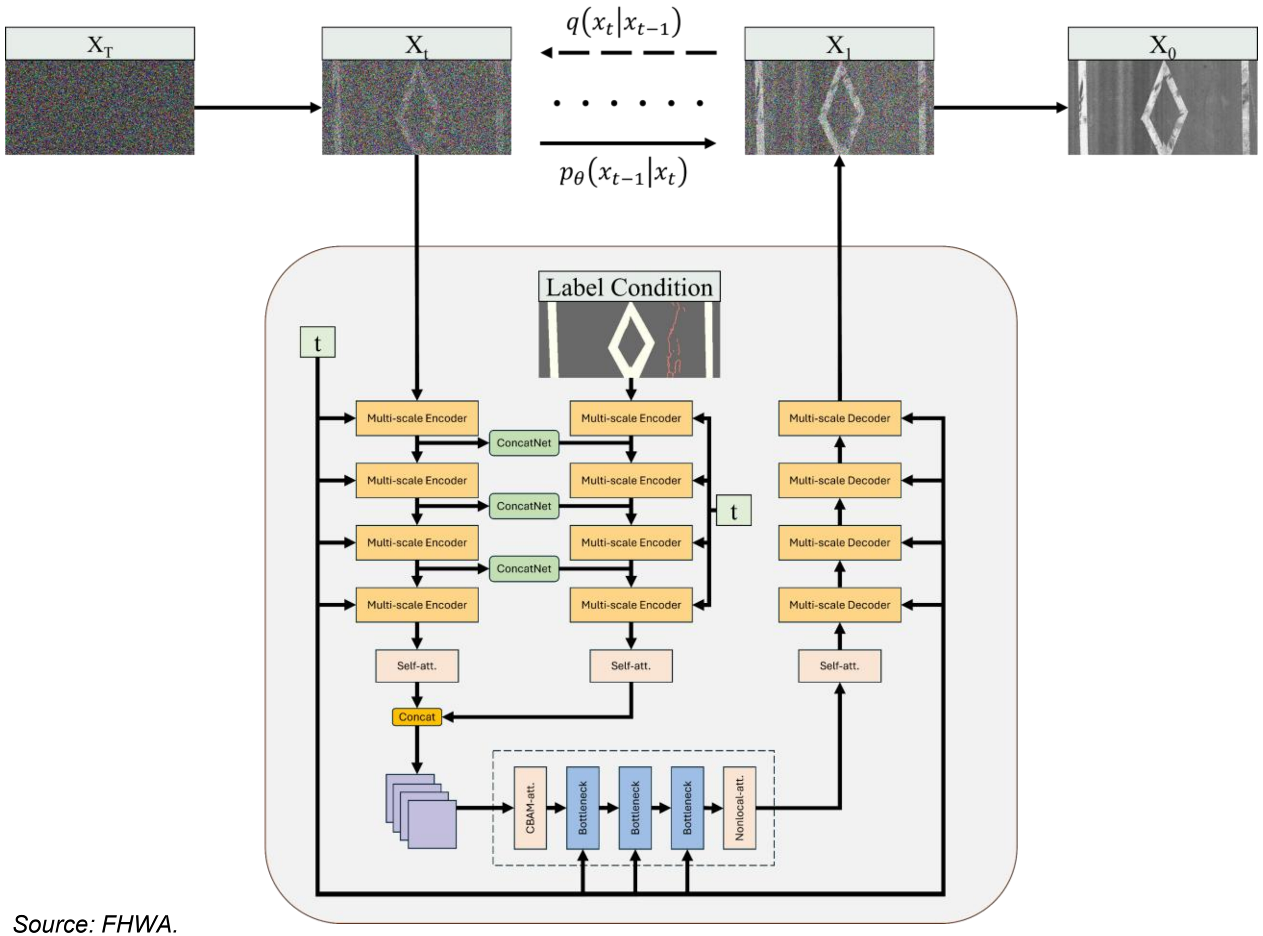
- Subpixel convolutions: "pixel-shuffle up-sampling operation" + "3×3 convolution with stride of 1."
- Anisotropic-stride 3×3 convolutions: only along transverse.



Source: FHWA.

Task 2: DL for Generating SR Texture Data: Diffusion Models

Introduction To Denoising Diffusion Model



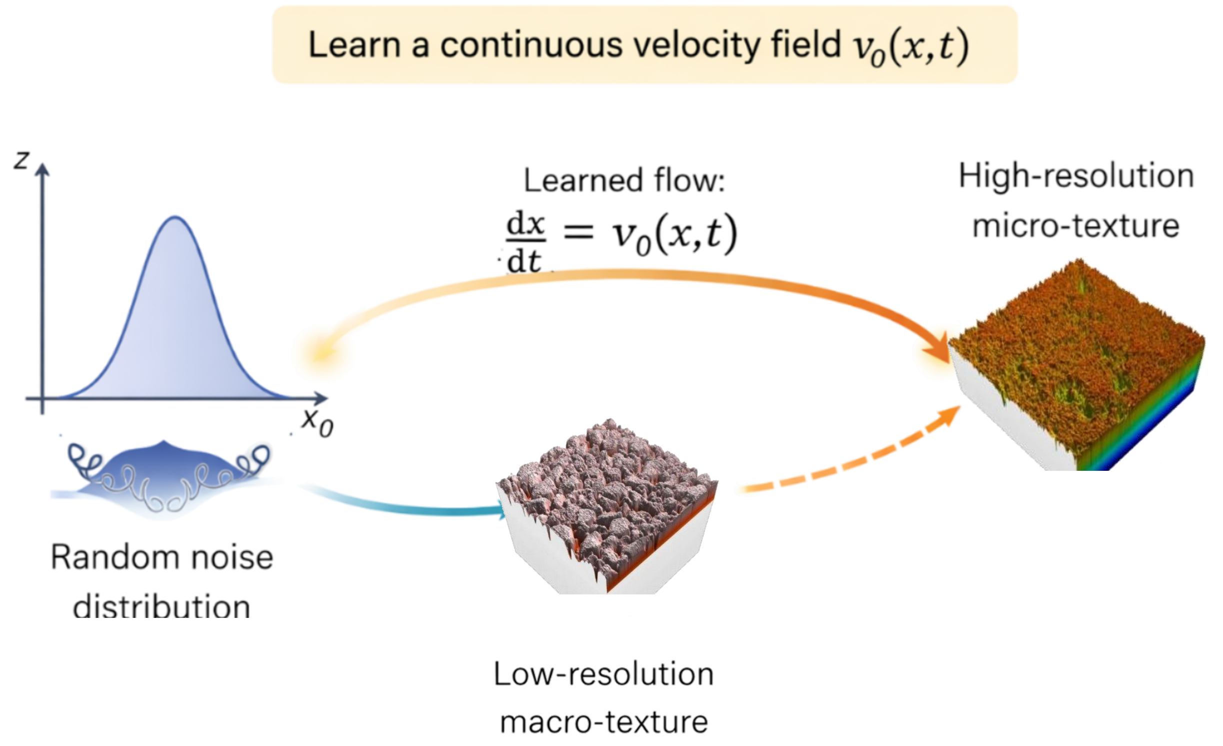
Source: FHWA.

Diffusion models generate images by learning to reverse a gradual noising process:

- Start with pure Gaussian noise and iteratively denoise it step by step.
- Recover realistic images with high fidelity and variety.

Task 2: DL for Generating SR Texture Data: Flow Matching

Introduction to Flow Matching



Source: FHWA.

- The flow matching process learns a continuous velocity field that smoothly transforms a simple distribution into the target data distribution.
- The learning equation: $\frac{dx}{dv} = v_0(x, t)$

Where:

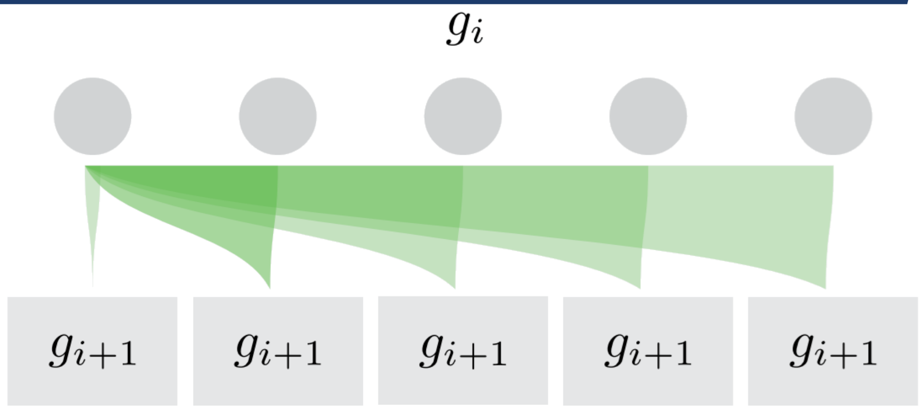
x = target signal.

t = time.

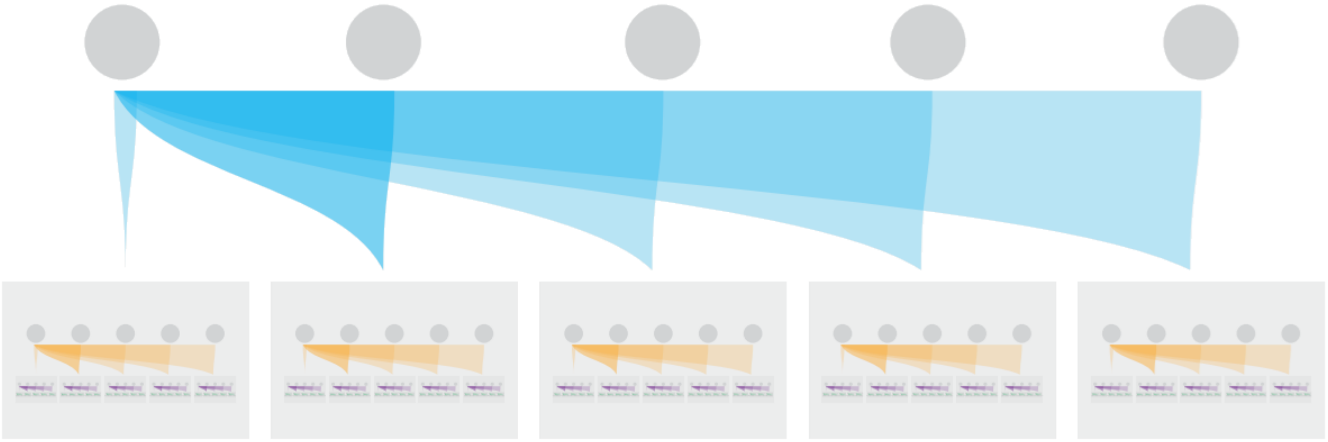
v_0 = learned velocity field.

Task 2: DL for Generating SR Texture Data: FGM Design

Generator



Fractal From the Generator

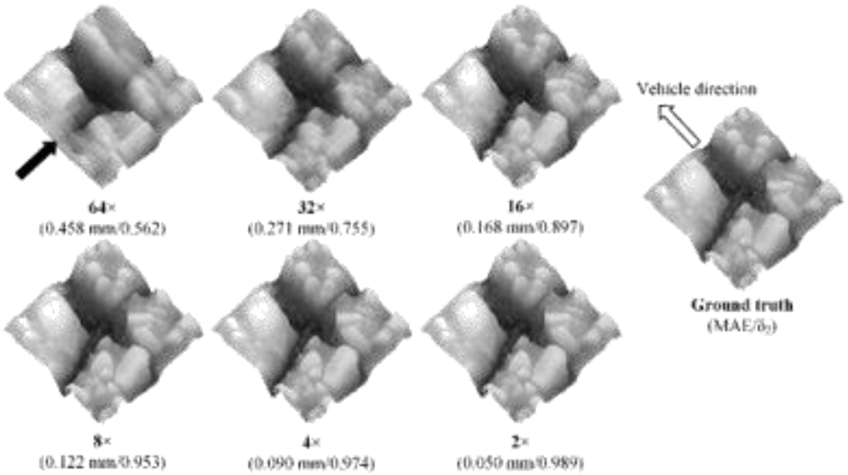


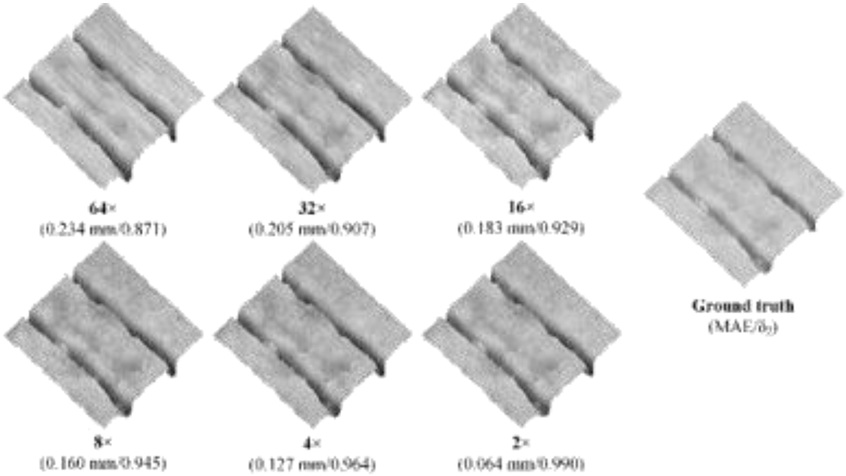
All images source: FHWA.

gi = generator.

- FGM abstracts a full generative model as an atomic module.
- Recursively composes these modules (generator-within-generator) into a self-similar, multilevel architecture.
- Factors high-dimensional image distributions into tractable subproblems, enabling pixel-level SR with strong modularity and efficiency.

Task 2: DL for Generating SR Texture Data: Example Images

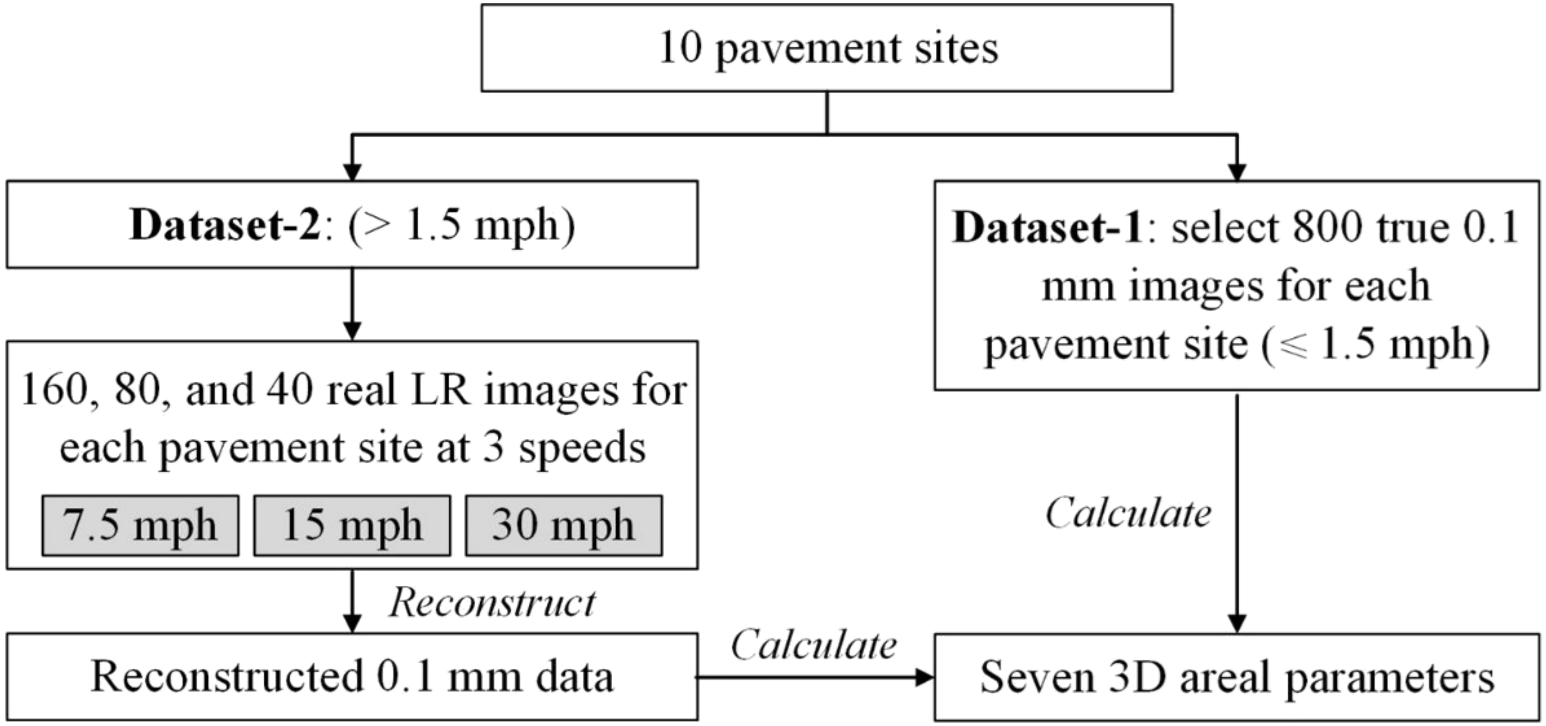




All images source: FHWA.

- Image reconstruction evaluation.
- Evaluation of each generative model at six fixed speeds.

Task 3: Novel Texture Indicators for Safety Evaluation: Texture Evaluation Scheme



Source: FHWA.

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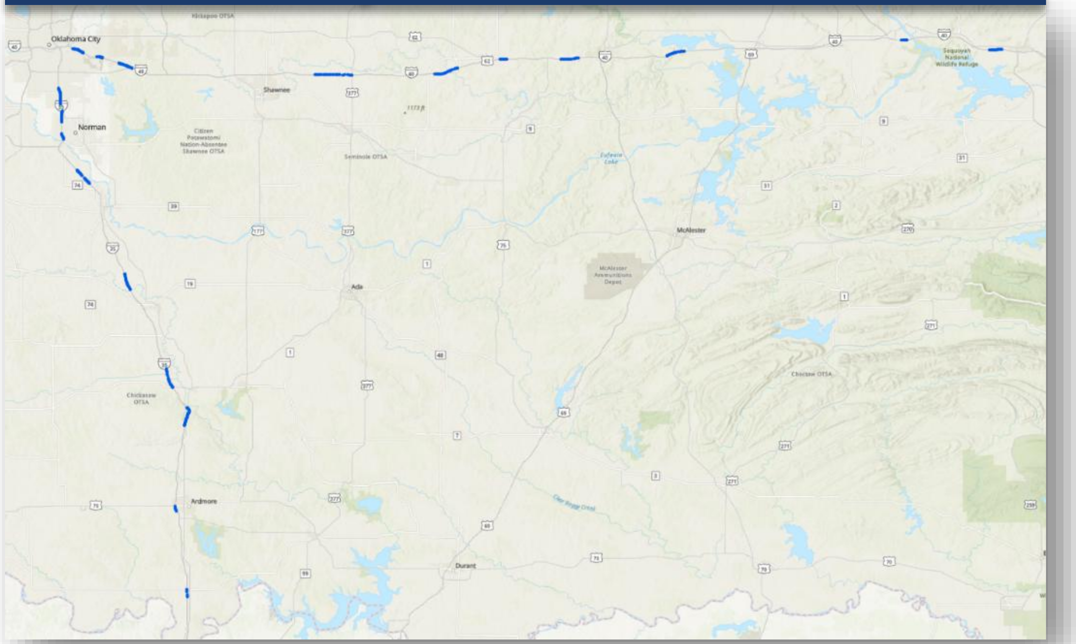
Task 3: Novel Texture Indicators for Safety Evaluation: Case Study

Case Study Subsection Locations



HWY	Subsection	Direction	Section Length (miles)	No. of 1-mm Images	No. of SR Images	Estimated Time for SR Data Generation (minutes)
I40	5568 00000560	W	1.01	619	207	27
I40	5568 00000200	W	1.2	734	245	31
I40	5568 00000123	W	0.67	411	138	18
I40	5422 00000000	W	3.96	2422	808	104
I40	6737 00000000	W	5.9	3609	1401	180
I40	5422 00001099	W	1.53	937	217	28
I40	5603 00000000	W	3.01	1841	767	98
I40	5568 00000200	E	1.15	704	235	30
I40	00000938	E	2.09	1279	496	64
I40	00000000	E	5.94	3633	1401	180
I40	5603 00000000	E	3.03	1854	720	92
I40	4607 00000500	E	3.01	1841	714	92
I35	1406 00000818	N	2.2	1334	375	48
I35	1406 00001035	S	1.1	662	221	28
I35	1406 00000818	S	2.2	1334	375	48
I35	1406 00000460	N	1.74	1058	353	45
I35	1406 00001035	N	1.1	662	221	28
I35	5032 00000159	S	3.59	2300	791	102
I35	1406 00000128	S	1.04	669	224	29
I35	1406 00000128	N	1.04	669	224	29
I35	4405 00001653	N	3.42	2062	688	88
I35	1406 00000460	S	1.74	1058	368	47
I35	5032 00000159	N	3.59	2300	788	101
I35	2546 00000000	S	3.8	2281	761	98
I35	2546 00002033	N	3.23	2031	678	87
I35	1036 00000620	S	0.94	593	198	25
I35	4317 00001383	S	1.53	954	319	41

HWY = highway.

Task 3: Novel Texture Indicators for Safety Evaluation: Parameter Introduction

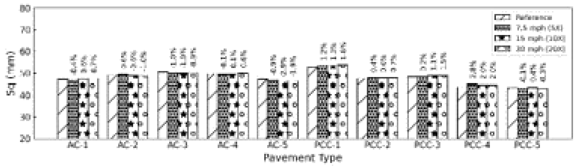
Parameter notation	Parameter name	Calculation equation
Sq	Root mean square height	$S_q = \sqrt{\frac{1}{A}\iint_0^A h^2(x,y)dxdy}$
Ssk	Skewness	$Ssk = \frac{1}{A \cdot S_q^3}\iint_0^A h^3(x,y)dxdy$
Sp	Maximum peak height	$Sp = \max_{(x,y)\in A}[h(x,y)]$
Sv	Maximum pit height	$Sv = \min_{(x,y)\in A}[h(x,y)]$
Spd	Peak density	$Spd = \frac{N_p}{A}$
Spc	Arithmetic mean peak curvature	$Spc = -\frac{1}{2n}\sum_{k=1}^{n}(\frac{\partial^2 h(x,y)}{\partial x^2} + \frac{\partial^2 h(x,y)}{\partial y^2})$
MTD	Mean texture depth	$MTD = \frac{1}{AK}\sum_{k=1}^{K}\iint_0^A[h_0 - h(x,y)]dxdy$

Source: FHWA.

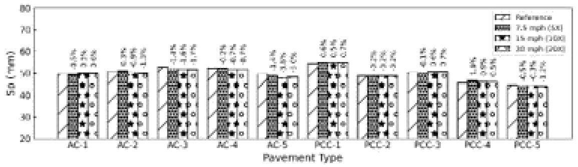
Relative errors: texture parameters between reconstructed deep submillimeter and true images:

$$\rho = \frac{S_r - S_g}{S_g} \times 100\%$$

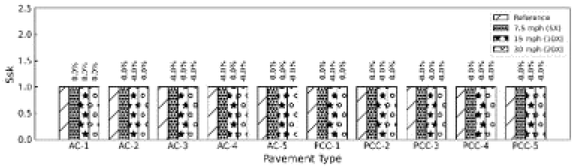
Task 3: Novel Texture Indicators for Safety Evaluation: Parameter Analysis



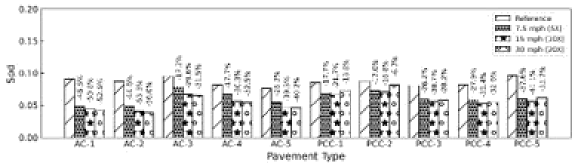
Sq and relative errors



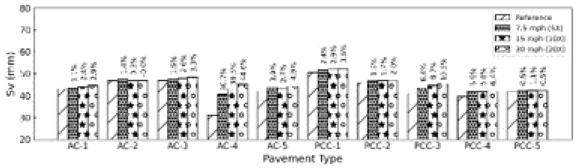
Sp and relative errors



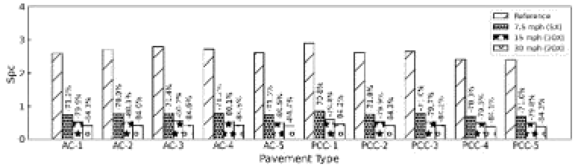
Ssk and relative errors



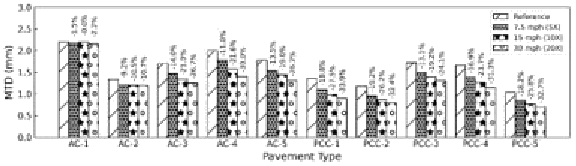
Spd and relative errors



Sv and relative errors



Spc and relative errors



MTD and relative errors

Parameters	The ρ of parameters (%)					
	7.5 mph (5×)		15 mph (10×)		30 mph (20×)	
	AC	PCC	AC	PCC	AC	PCC
Sq	-0.4	0.9	-0.8	1.1	-0.5	1.1
Ssk	0.0	0.0	0.0	0.0	0.0	0.0
Sp	-0.6	0.3	-1.3	0.3	-1.2	0.2
Sv	6.2	3.2	7.4	3.9	8.9	4.5
Spd	-31.0	-25.5	-40.7	-29.7	-42.6	-23.5
Spc	-71.2	-70.8	-80.1	-79.7	-84.5	-84.2
MTD	-9.5	-16.9	-14.1	-24.1	-19.0	-30.4

All images source: FHWA.

Task 3: Novel Texture Indicators for Safety Evaluation: Safety Performance Function Development

Poisson Model for Crash Frequency

- Highway crash counts are random, discrete, and nonnegative.
- The Poisson model is widely used for safety analysis and crash prediction.
- The probability is that segment *i* has y_i.

$$P(y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}$$

Where: λ_i predicts crash count for segment *i*, equal to the expected annual number of crashes $E[y_i]$.

Log-Linear Form of the Poisson Model

- Poisson parameter λ_i is specified as a function of explanatory variables X_i
- Common functional form: log-linear model

$$\log(\lambda_i) = \beta X_i$$

- Expected crashes on segment *i*:

$$E[y_i] = \lambda_i = \exp(\beta X_i) = \exp(\beta_0 + \beta_1 X_i + \cdots + \beta_\kappa X_{\kappa i})$$

Where:
B_0 = intercept
β_κ = regression coefficients
$X_{\kappa i}$ = explanatory variables for observation *i*.

- Maximum likelihood estimation is used to estimate β.

Model Assumptions and Data Preparation

- Poisson model assumption:
  - Crash count y_i follows a Poisson distribution.
  - Mean equals variance of crash counts.
- For each segment:
  - Total crashes over the study period are recorded.
  - Data are linked with surface texture parameters
  - Data preparation enables a localized and more accurate assessment of the relationship between the pavement condition and the crash risk.

Task 3: Novel Texture Indicators for Safety Evaluation: Results Analysis

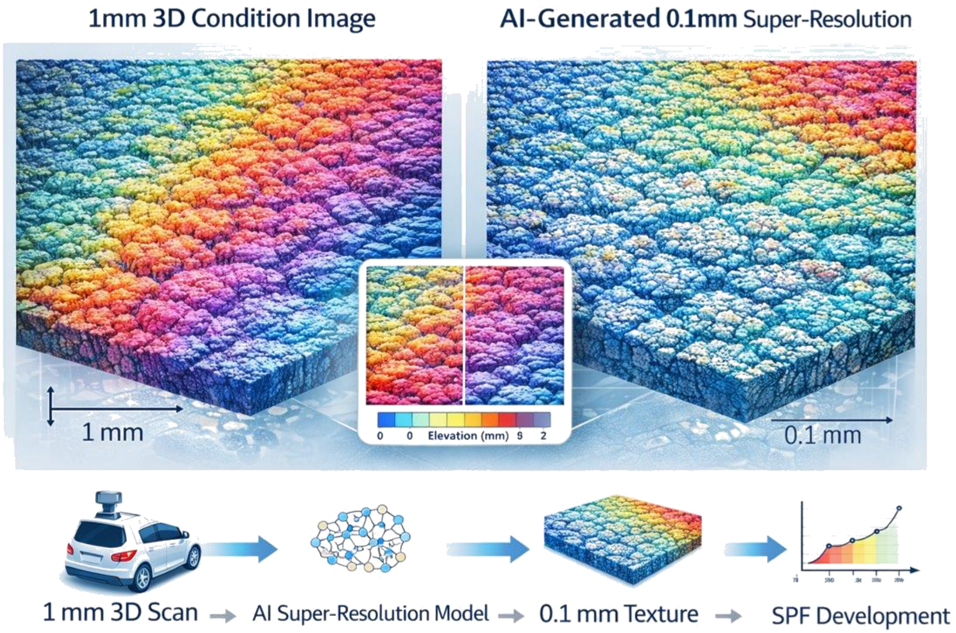
Variable		Coefficient	Standard Error	Z-value	$P>\|z\|$	Significance	Category
Intercept		13.7087	3.4428	3.9819	0.0001	**	Constant
AADT		3.9018E-06	0.0000	2.4382	0.0148	*	Traffic
Speed limit		−0.1320	0.0169	−7.7909	0.0000	***	Traffic
Rutting		5.76770	1.2378	4.6596	0.0000	***	Condition
Microtexture	S_q	−1116.8310	118.3879	−9.4337	0.0000	***	Height
	S_{sk}	0.5284	0.0551	9.5877	0.0000	***	Height
	S_v	−245.6202	40.5796	6.0528	0.0000	***	Height
	S_a	356.2303	100.7371	−3.5362	0.0004	**	Height
	S_t	241.9016	50.0184	4.8363	0.0000	***	Height
Macrotexture	MPD	2.1083	0.2385	8.8413	0.0000	***	Height
	SBI	9.0072	1.2636	7.1283	0.0000	***	Feature
	SAR	−16.2668	2.1237	−7.6595	0.0000	***	Hybrid
Note: Significance codes: 0 = *; 0.001 = **; 0.01 = *; 0.05 = . ; AIC = 754.23, Log-Likelihood = -365.117, RMSE: 5.034, and R^2: 0.5432**							

AADT = annual average daily traffic; AIC = Akaike information criterion; SAR = synthetic aperture radar; SBI = surface bearing index.

Demonstrate a good fit with a Pseudo R^2 of 0.5332, an AIC of 671.66, and an RMSE of 4.32.

3.3. Conclusions

- This framework enables high-fidelity, texture-based safety assessments at highway speeds and provides a practical data-driven approach to pavement safety management that considers both macrotextures and microtextures.
- Four categories of SR generative models are systematically evaluated, and the best-performing model is selected to enable accurate microtexture reconstruction at highway speeds.
- Five categories of safety performance models are developed for texture-based safety assessments at highway speeds.



All images source: FHWA.

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THE SAFE SYSTEM APPROACH

Zero is our goal. A Safe System is how we get there.

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