Deep Residual Network Architecture for Pavement Skid Resistance Prediction

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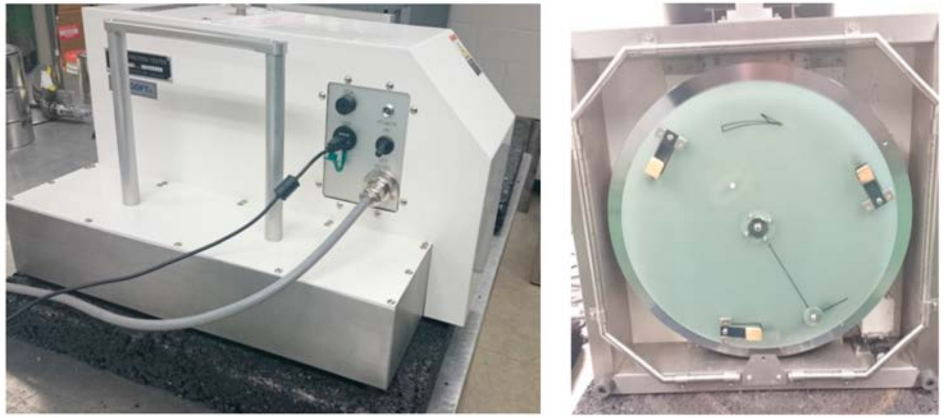
Background

- ❑Roadway departure: accounting for 53% of the total traffic fatalities in the U.S. (FHWA 2017)
- ❑25% of all European road fatalities related to diminished skid-resistance
- ❑Desired pavement friction: effective countermeasure to roadway departure fatalities

Background

- ❑Pavement friction: the force resisting the relative motion between vehicle tire and pavement surface
  - ✓ Deteriorate with time under various factors
  - ✓ Some DOTs perform continuous monitoring
  - ✓ Friction Testing: British pendulum tester (BPT), dynamic friction tester (DFT), grip tester, locked-wheel trailer, Side-Force Coefficient Road Inventory Machine (SCRIM), etc.



DFT

BPT

Background

Locked-wheel Tester

Grip Tester

SCRIM

Background

- ❑Existing friction measurements
  - ✓ Require testing tire/rubber
  - ✓ Require large water tank to wet the surface
  - ✓ Disturbs the traffic flows during the tests
  - ✓ Performed at project level
  - ✓ Affected by temperature, test speed, contact pressure, water film depth, tire tread, viscoelastic properties of testing tires et al.

- Predict pavement friction using non-contact measurements:

  Challenging

Background

- ❑Pavement texture: the deviations of pavement surface from a true planar surface
- ❑High speed profiler
  - ✓ Collect texture data at highway speed and network level
  - ✓ Non-contact method
  - ✓ Widely implemented by DOTs

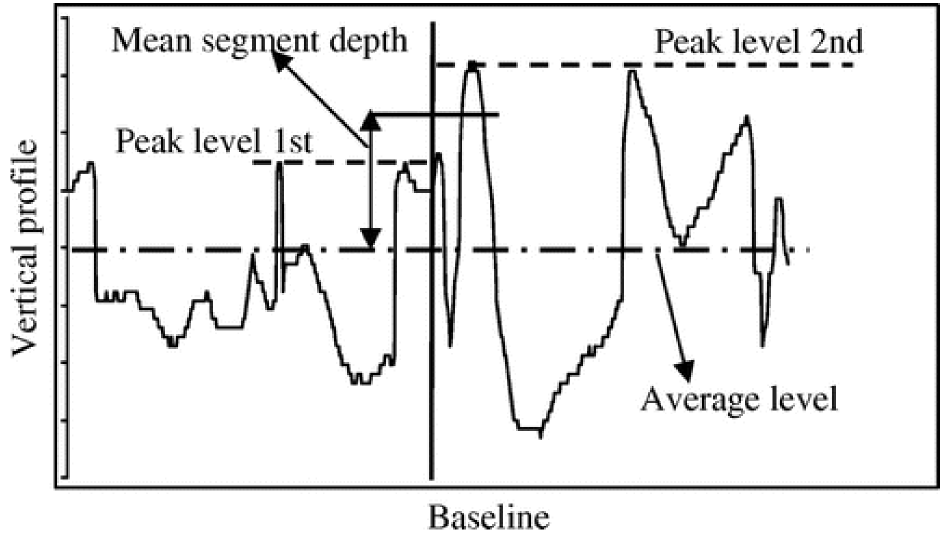
- Predict pavement friction from the high speed profiler data:

  Could be a surrogate of tradition friction testing

Problem Statement

- ❑No consistent relationships between texture indicators and friction via traditional methodologies
  - ✓ Macro-texture
    - ❖ MPD: simplified representation of rich texture profiles
    - ❖ MTD: labor and time consuming, require traffic control, and subjective
  - ✓ Micro-texture: lab testing on limited area, high speed instrument not available

MPD Calculation in ASTM



Problem Statement

- ❑ Machine-learning (ML) technology
  - ✓ Fail to process natural data in its raw form
  - ✓ Require domain experts to pre-process the input data
  - ✓ Developing customized feature extractor(s)
- ❑ Deep learning (DL) neural networks
  - ✓ Allow a machine to be fed with raw data
  - ✓ Automatically discover the representations needed for detection or classification
  - ✓ Led to many breakthroughs for image classification and recognition
  - ✓ However, deeper neural networks were much more difficult to train than expected: degradation problem

Objectives

❑Deep Residual Network Architecture for pavement skid resistance prediction

- ✓ Use non-contact high speed texture measurement to predict pavement friction
- ✓ Learn and extract the textural features and classification boundaries automatically from raw input data
- ✓ "Convolutional group" and "skipped connection" perfectly solves the problem of "degradation"
- ✓ Develop Friction-ResNets model with 11 convolution layers: high prediction accuracy

Data Source

FHWA, LONG TERM PERFORMANCE MONITORING OF HIGH FRICTION SURFACING TREATMENTS (HFST) SITES (3 YR)

Data Source

Distribution

- **49 HFST Sites**
- **In 12 states**

Devices

- **High Speed Profiler**
- **Grip Tester**

(a) HFST from WV-I77

(b) AC from KY-605

(c) PCC from OK-I44

(d) Grooved AC from MO-I44

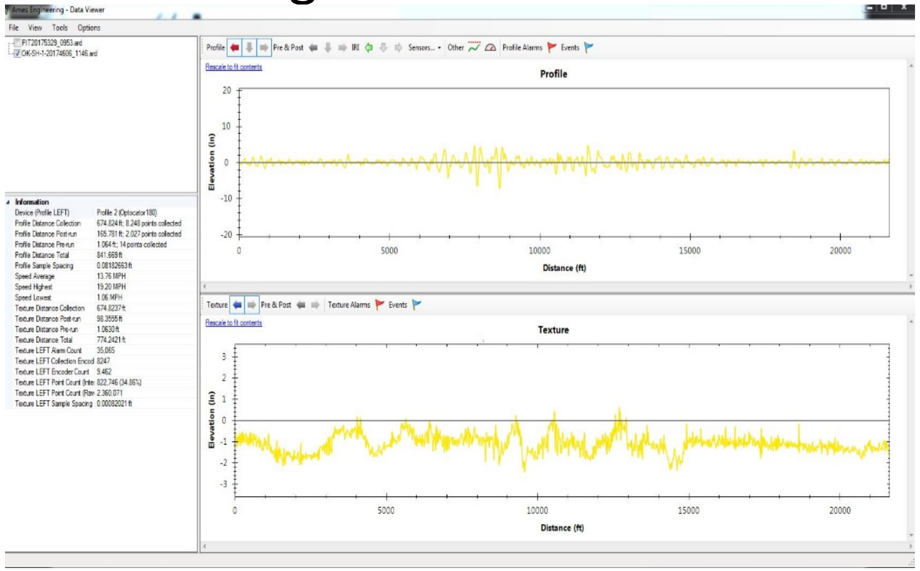
(e) Grooved PCC from IA-I80-Ramp

(f) Bridge Deck from TN-SR385

Data Collection Devices

❑AMES 8300 High Speed Profiler

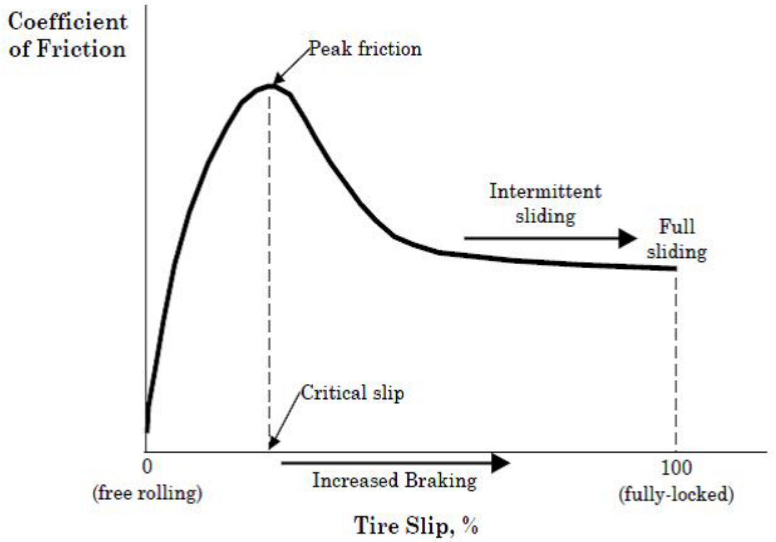
- ✓ Surface macro-texture data & standard profile data at highway speed (25 - 65 mph)
- ✓ Mean Profile Depth (MPD) & roughness index (IRI)
- ✓ Resolution: 0.045 mm in vertical direction and 0.5 mm profile wavelength.



Data Collection Devices

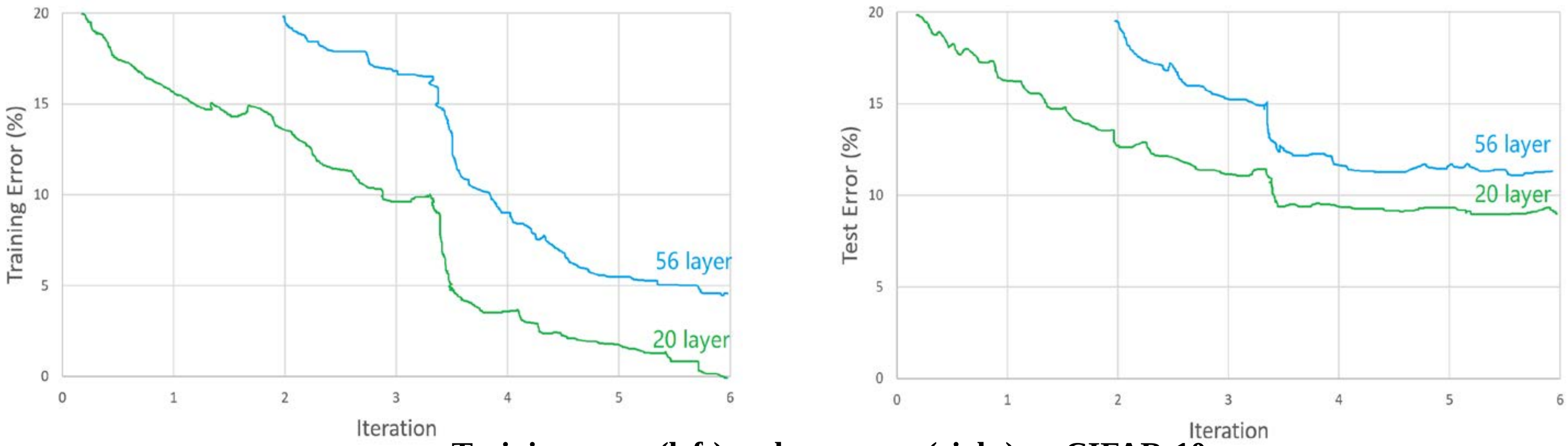
❑Grip Tester

- ✓ Continuously friction measurement equipment (CFME)
- ✓ Operating around the critical slip of an anti-lock braking system (3.28-ft intervals, 40 mph testing speed and a constant water film thickness of 0.25 mm)
- ✓ Airports and highways safety management



Deep Residual Networks (ResNets)

- ❑Newest trends in Artificial Intelligence: deep learning (DL)
- ❑Top-ranked teams on ImageNet challenging all exploit “very deep” models
- ❑Predict friction using non-contact texture measurements
- ❑Deeper neural networks are much more difficult to train than expected: exploding/vanishing gradient problem



Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer networks (He et al. 2016)

Deep Residual Networks (ResNets)

- Lower gradients: circumvent the exploding gradient problem
- "Skipped connection" & "residual unit": solve the "vanishing" problem
- Residual unit performs the following computation

$$X_{i+1} = X_i + F(X_i, W_i)$$

X_i :input feature to the i^{th} residual unit.

$W_i = \{W_{i,k} | 1 \leq k \leq K\}$: a set of weights (and biases) associated with i^{th} residual unit

K: number of layers in a residual unit.

Function *F*: denotes the type of residual work in each unit

Deep Residual Networks (ResNets)

❑This process can be repeated recursively

$$X_{i+2} = X_{i+1} + F(X_{i+1}, W_{i+1})$$
$$X_{i+2} = X_i + F(X_i, W_i) + F(X_{i+1}, W_{i+1})$$

❑For any deeper unit and any shallower unit

$$X_I = X_i + \sum_{k=i}^{I-1} F(X_k, W_k)$$

❑Assigning loss function e, according to the chain rule of backpropagation

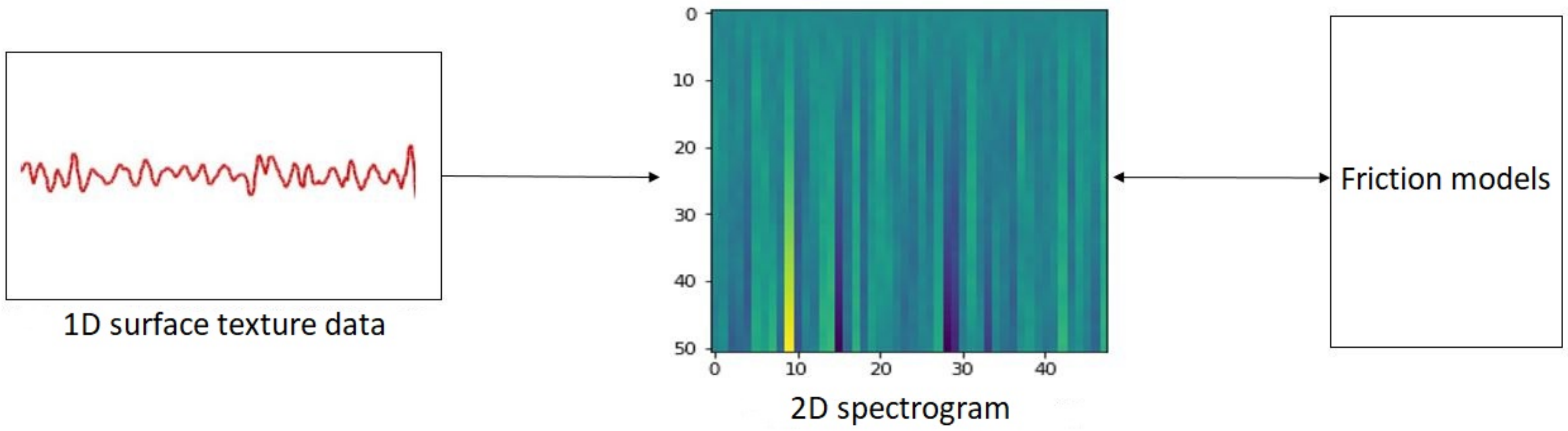
$$\frac{\partial e}{\partial X_i} = \frac{\partial e}{\partial X_I}\frac{\partial X_I}{\partial X_i} = \frac{\partial e}{\partial X_I}\left(1 + \frac{\partial}{\partial X_i}\sum_{k=i}^{I-1} F(X_k, W_k)\right)$$

- $\frac{\partial e}{\partial X_I}$ propagates information backward directly without any weight layer within a unit
- Information arrives at any shallower unit *i*, while the term $\frac{\partial e}{\partial X_I}\frac{\partial}{\partial X_i}\sum_{k=i}^{I-1} F$ propagates through the weight layers within a unit
- Gradient of a stage can't vanish, since $\frac{\partial}{\partial X_i}\sum_{k=i}^{I-1} F$ cannot always equal to -1 for all samples in a mini-batch

Profile Spectrogram

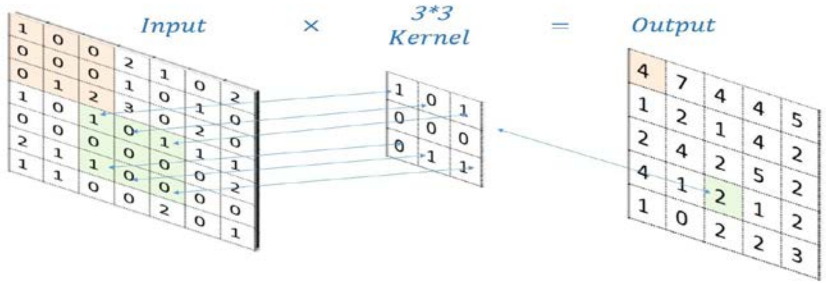
- ❑Pair raw pavement texture profile with friction number for each 3.28-feet segment

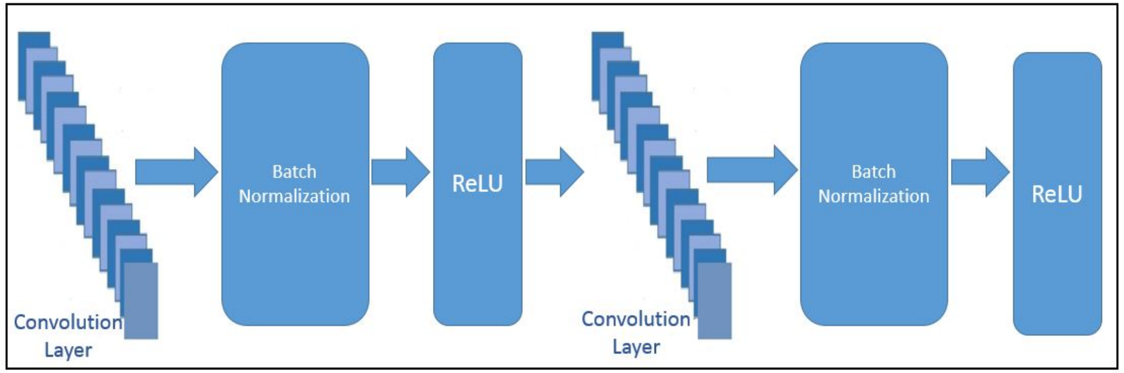
- ❑Spectrogram: a visual representation of the spectrum of signal frequencies as they vary with time or some other variable



Convolutional Group

- ❑Convolution: adding each element of the 2D matrix to its local neighbors, weighted by the 3*3 kernel





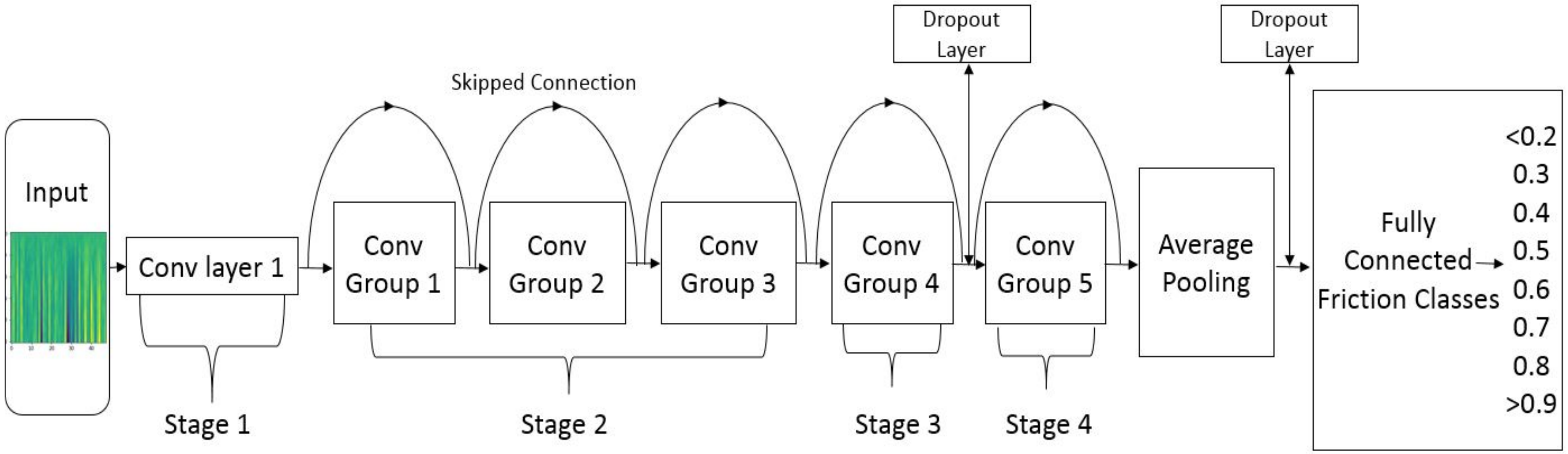
- ❑BN: makes normalization a part of the model architecture performs the normalization for each training mini-batch
- ❑ReLU: most commonly used activation function in DL
  - ✓ Helps a network account for interaction
  - ✓ Capture non-linearity's characteristics so as to improve discriminative performance

Friction-ResNets Architecture

❑Frcition-ResNets architecture

- ✓ 13 layers: 11 convolution, 1 average pooling, and 1 output layer

Stage Name	Stage 1	Stage 2	Stage 3	Stage 4	Average pooling
Output Size	51*48	51*48	25*24	12*12	1*1
Number of kernels (3*3)	16	32	64	96	-
Number of Conv Units	1 conv layer	3 conv groups	1 conv group	1 conv group	-

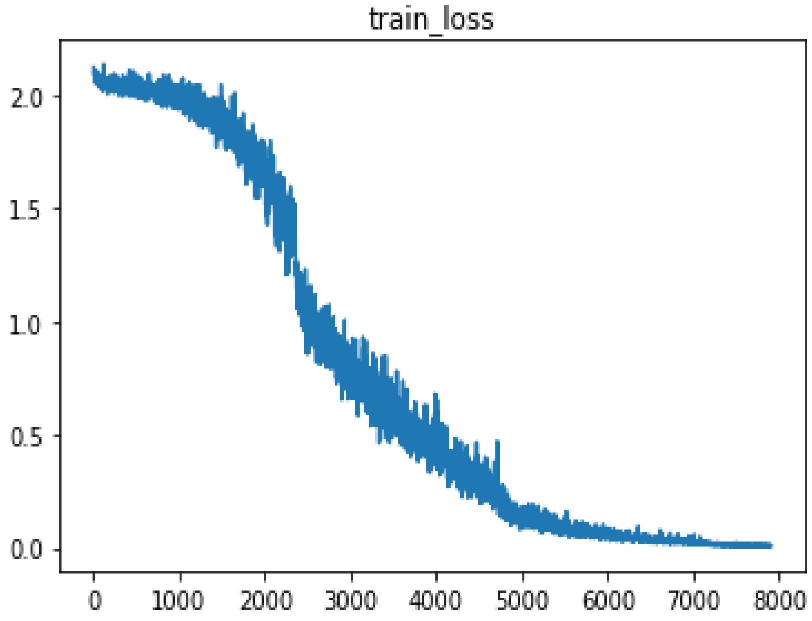


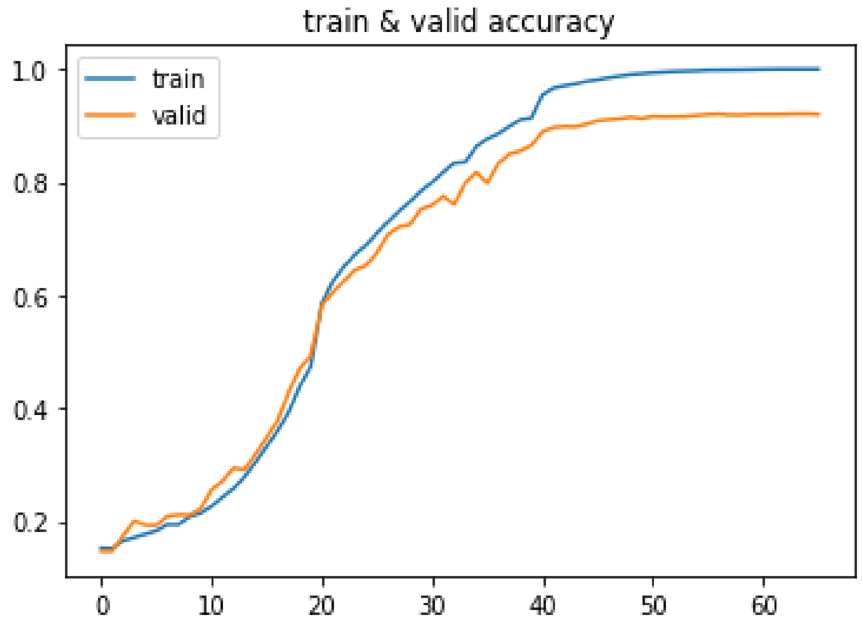
Training/Validation/Test

- ❑Eight bins at every 0.1 interval ranging from 0.2 to 1.0
  - ✓ <0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, >0.9
- ❑4,200 pairs of data randomly selected from each bin of friction level
  - ✓ 70%, 15% and 15% for training, validation, and testing
- ❑Training platform: Pytorch
- ❑Training hardware: Intel (R) Core (TM) i7-4702HQ CPU @ 2.20 GHz
- ❑Training time: 9.2 hours with 8000 iterations (65 epochs)

Learning Curve

- ❑8000 iterations (65 epochs)
- ❑Training accuracy: 99.85%
- ❑Validation accuracy: 91.95%





Testing Results Evaluation

Testing Distribution		Predicted Friction Level							
		<0.2	0.3	0.4	0.5	0.6	0.7	0.8	>0.9
Actual Friction Level	<0.2	579	11	10	9	12	3	2	4
	0.3	11	565	10	12	11	9	8	4
	0.4	10	17	568	8	7	4	8	8
	0.5	11	5	9	582	7	5	7	4
	0.6	1	8	7	8	590	9	6	1
	0.7	2	2	11	3	12	588	7	5
	0.8	3	10	15	10	6	16	551	19
	>0.9	3	6	5	5	4	9	19	579

Test accuracy: 91.3%

Comparisons with Machine Learning (ML) Algorithms

- ML: most effective classification tool before widespread adoption of deep learning
- State-of-the-art ML algorithms: Support Vector Machines (SVM) & Random Forest (RF)
- Traditional ML algorithms: K-Nearest Neighbor (KNN) & Gaussian Naïve Bayes (GNB)

Conclusions

- ❑ Large amount of texture and friction data collected on diverse pavement surfaces
    - ✓ 23,520 pairs of data for training, 10,080 pairs of data for validation and testing
- ❑ Friction-ResNets: ResNets based friction prediction model
    - ✓ 11 convolutional layers with millions parameters
    - ✓ Achieve 99.85% training accuracy, 91.95% validation accuracy and 91.3% testing accuracy
    - ✓ Outperform other machine learning algorithms
    - ✓ Using non-contact texture measurements to predict friction

Thanks and Questions?

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