HOW FDOT IS USING MACHINE LEARNING TO DETECT RAVELING FROM 3D IMAGES

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OUTLINE

- Background
- Challenges from windshield survey
- Machine learning for raveling detection
- Implementation and benefits
- Future applications

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BACKGROUND

What is an 3D Automated Distress system?

What is raveling?

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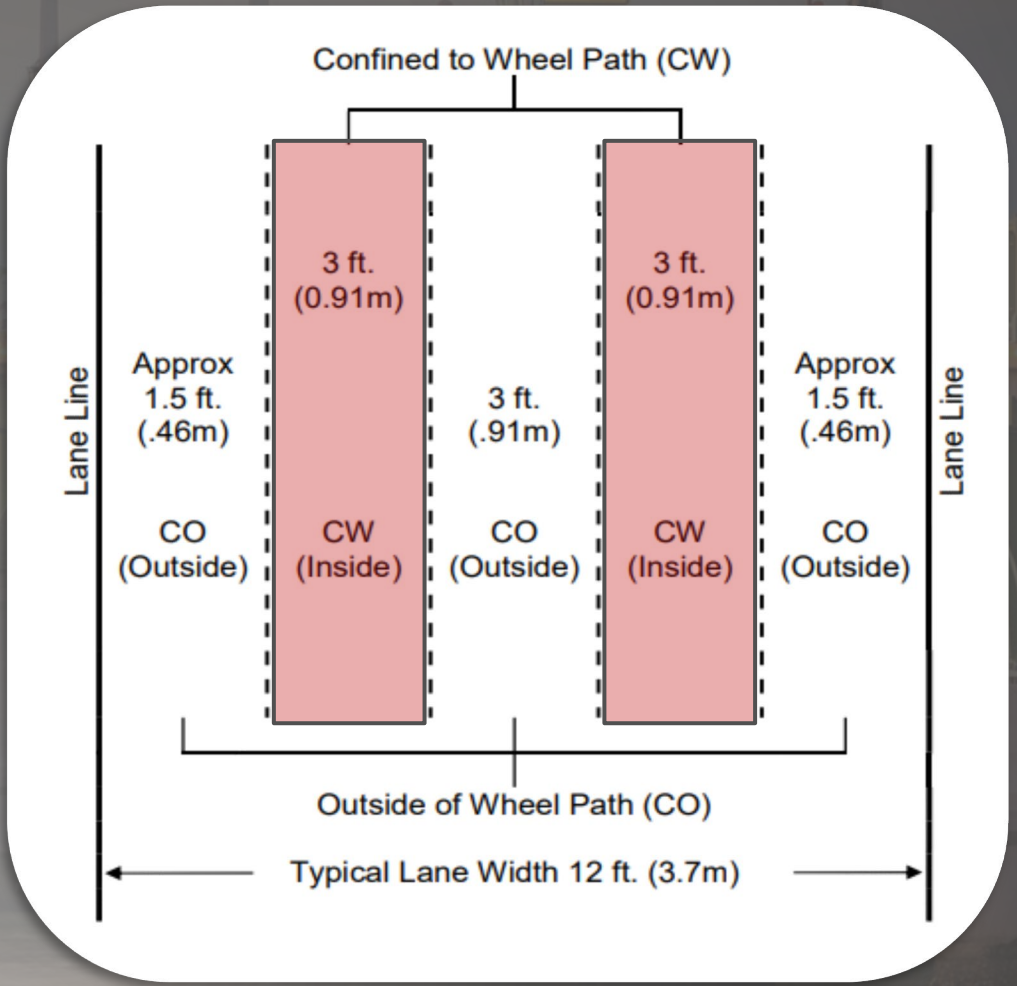
• CHALLENGES FROM WINDSHIELD SURVEY

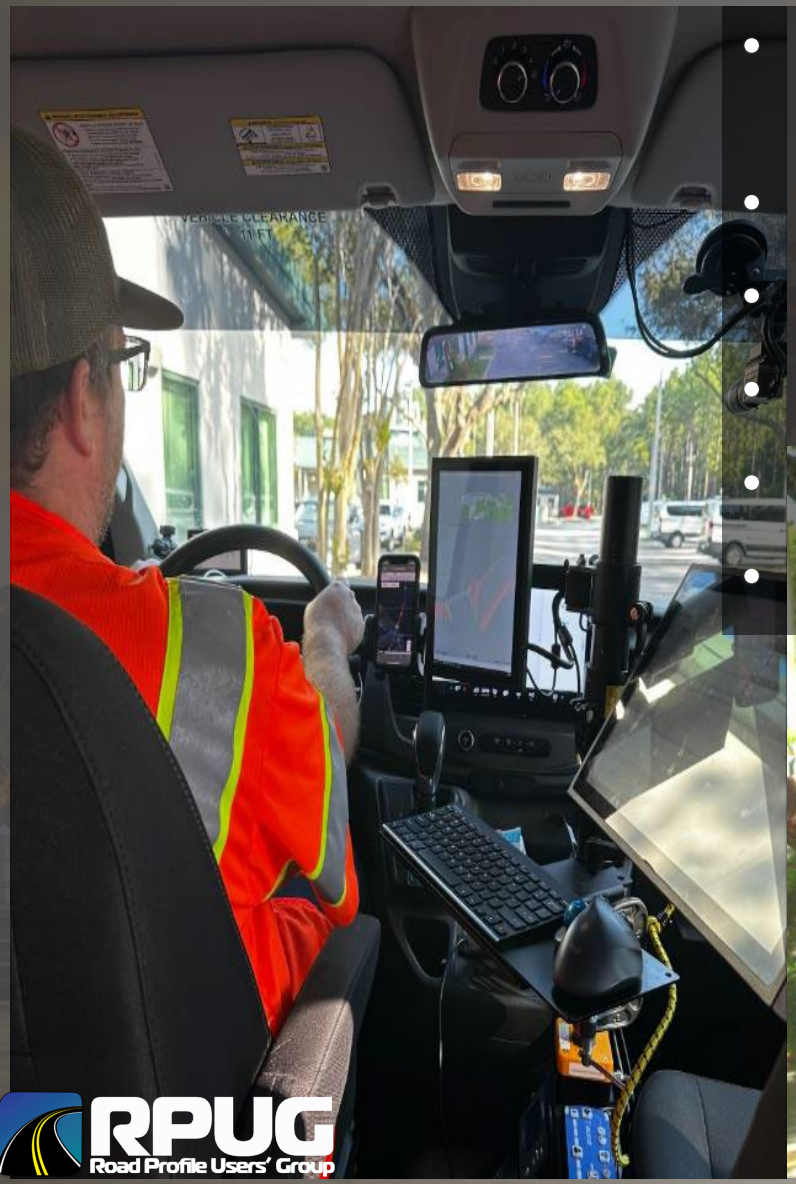
LIMITATIONS AND DRAWBACKS OF WINDSHIELD SURVEYS FOR RAVELING DETECTION

PERCENT OF PAVEMENT AREA AFFECTED BY CRACKING	CONFINED TO WHEEL PATHS (CW) *PREDOMINANT CRACKING CLASS*		
	CLASS I CRACKING Width < 1/8"	CLASS II CRACKING 1/8" < Width ≤ 1/4"	CLASS III CRACKING Width > 1/4" (Including Raveling & Patching)
	DEDUCT	DEDUCT	DEDUCT
0 – 5	0.0	0.5	1.0
6 – 25	1.0	2.0	2.5
26 – 50	2.0	3.0	4.5
51+	3.5	5.0	7.0

PERCENT OF PAVEMENT AREA AFFECTED BY CRACKING	OUTSIDE OF WHEEL PATHS (CO) *PREDOMINANT CRACKING CLASS*		
	CLASS I CRACKING Width < 1/8"	CLASS II CRACKING 1/8" < Width ≤ 1/4"	CLASS III CRACKING Width > 1/4" (Including Raveling & Patching)
	DEDUCT	DEDUCT	DEDUCT
0 – 5	0.0	0.0	0.0
6 – 25	0.5	1.0	1.0
26 – 50	1.0	1.5	2.0
51+	1.5	2.0	3.0



• CHALLENGES FROM WINDSHIELD SURVEY



- Not easy to determine crack width & extent while driving at traffic speed
- Subjective & rater dependent
- Assigned as representative condition of entire section
- Same rating for wide range of distress amount
- Not ideal for performance modeling
- Crack rating can plateau for several years

% Distress Area
01 – 05
06 – 25
25 – 50
51+

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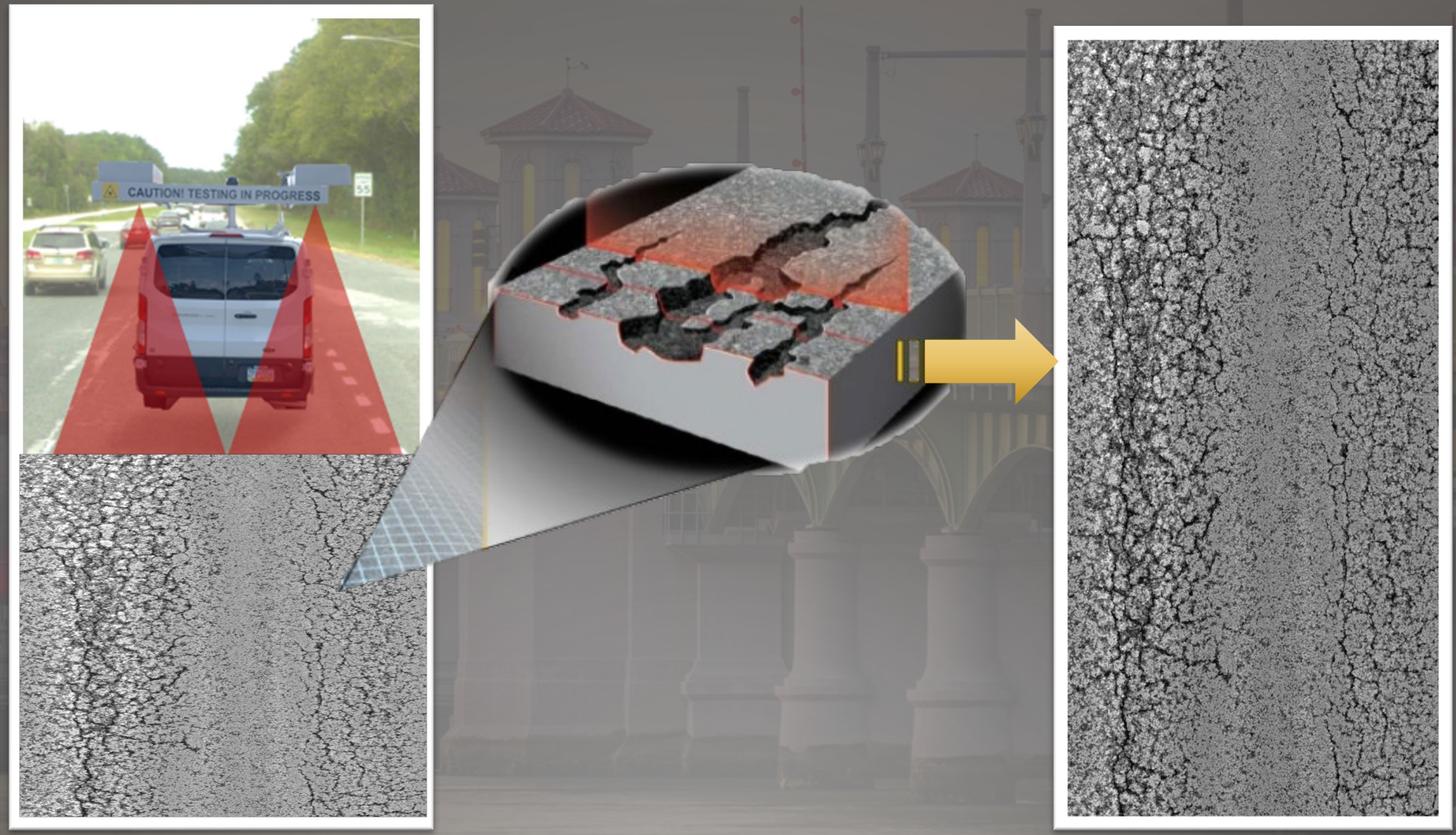
MACHINE LEARNING FOR RAVELING DETECTION



MACHINE LEARNING FOR RAVELING DETECTION

- It is not a Large Language Model (LLM) – ChatGPT, Gemini, Copilot
- It is not Convolutional Neural Networks (CNN)
- It is a Random Forest Classifier (RFC)

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RANDOM FOREST ALGORITHM

- Forest of Trees: Enhanced model robustness through the combination of multiple decision trees.
- Diversity through Randomness: Each tree utilizes a random subset of features, promoting diverse learning and mitigating overfitting.
- Voting Power: Utilizes majority voting for classification tasks and average prediction for regression tasks.
- Strength in Numbers: Randomness in tree creation lowers model variance, thereby boosting accuracy.

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RANDOM FOREST ALGORITHM

Manual ratings of training set images

Define the random forest model (hyper-parameters)

Identification and extraction of input parameters from training set (images)

Building the random forest classifier (estimators)

Extraction of input parameters from production data (images)

Use the random forest classifier to classify the production data

Output the classification to the SQL database and .csv file

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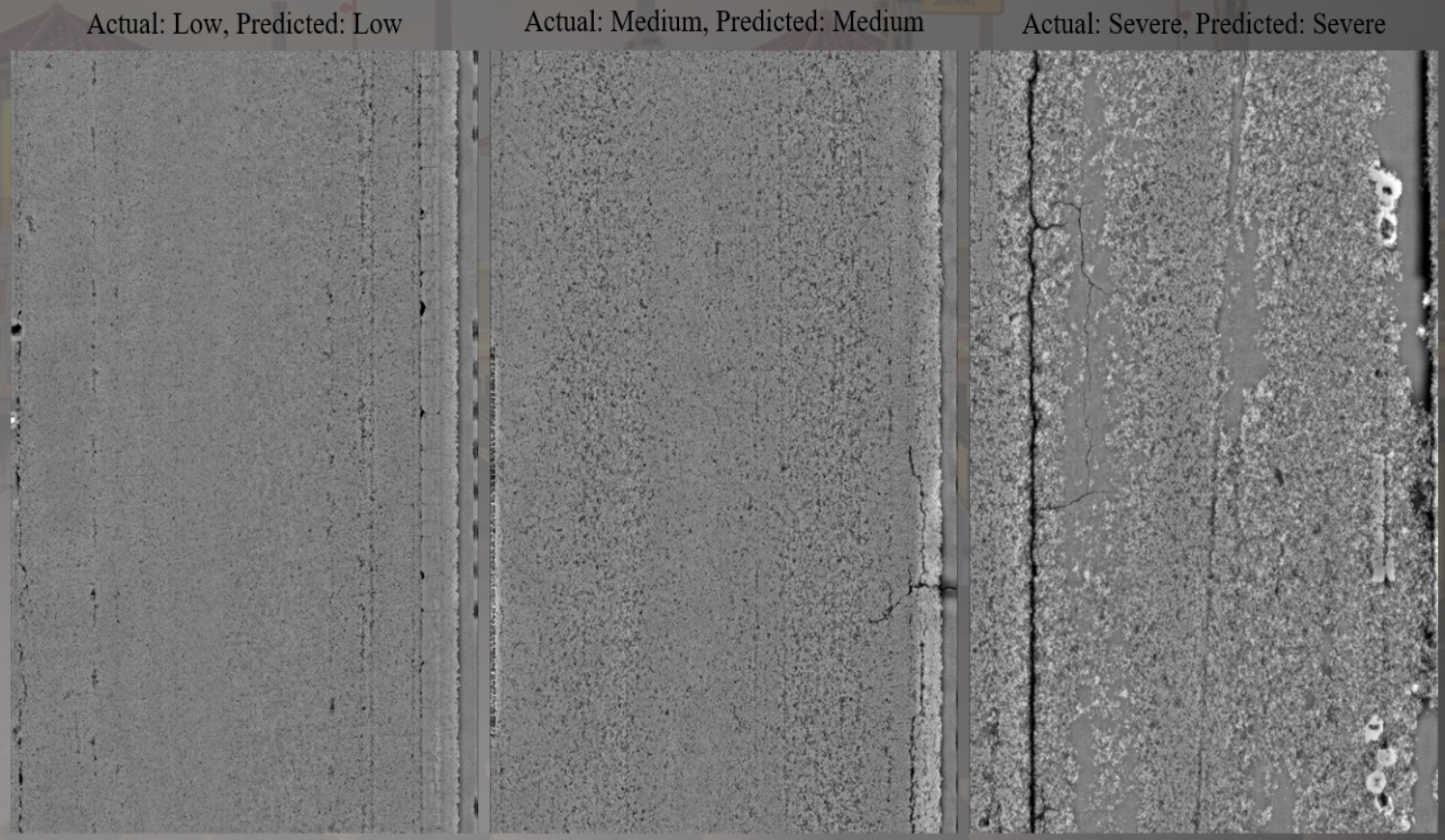
MANUAL RATINGS OF TRAINING SET IMAGES



3021 LCMS pavement images

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RFC HYPERPARAMETERS

- Library: scikit-learn (Python)
- Classifier: RandomForestClassifier
- Number of Trees (Estimators): 1000
- Evaluation Metric: Out-of-Bag Accuracy
- Tree Building: Gini impurity test with bootstrapping
- Train/Test Split: 67% training / 33% testing

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IDENTIFICATION AND EXTRACTION OF INPUT PARAMETERS FROM IMAGES

Feature	Formula
Arithmetic mean	$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$
Standard deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$
Root mean square	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2}$
Skewness	$Sk = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \bar{x})^3}{\sigma^3}$
Kurtosis	$K = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \bar{x})^3}{\sigma^3}$
Interquartile range	$IQR = Q_3 - Q_1$

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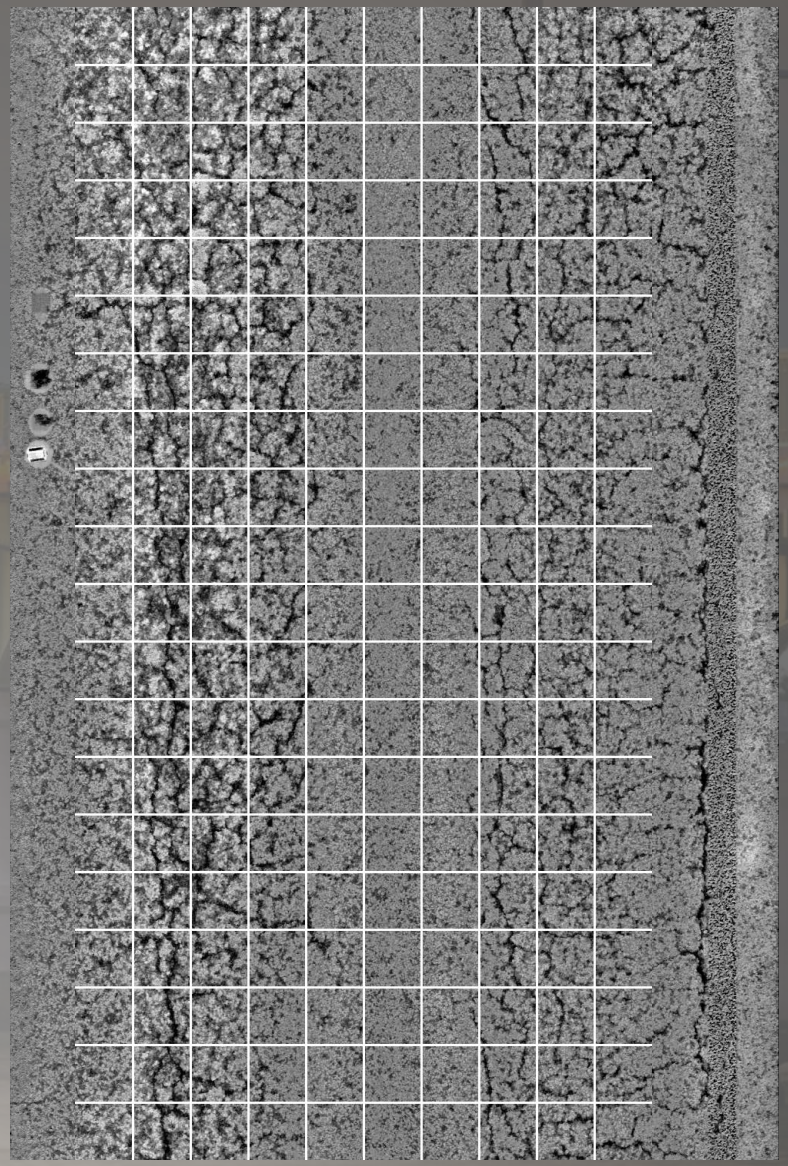
EXTRACTION OF INPUT PARAMETERS FROM IMAGES

- Pixel values from 0-255
- Lighter pixels represent higher elevations (z-coordinates)
- Image size 1020 by 1524 – about 13ft by 20ft
- Each pixel is 4 mm
- Statistical information based on the pixel values is used to generate a 606-length vector for each image



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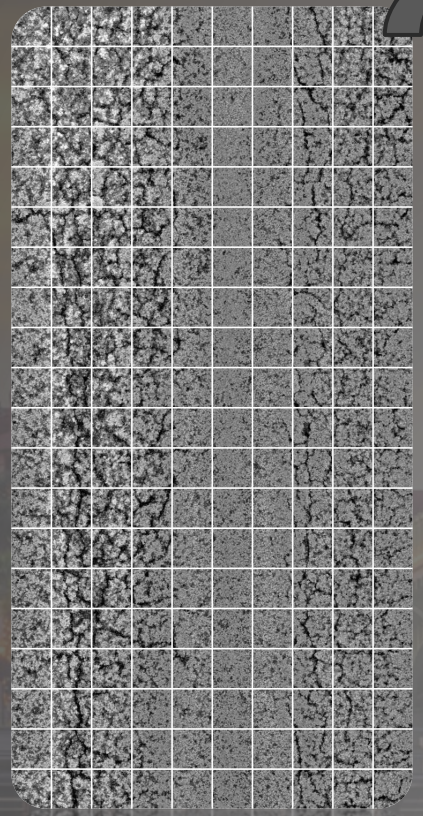
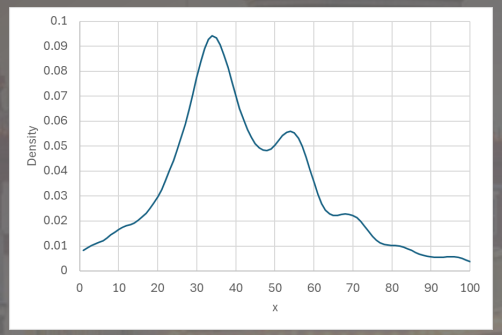
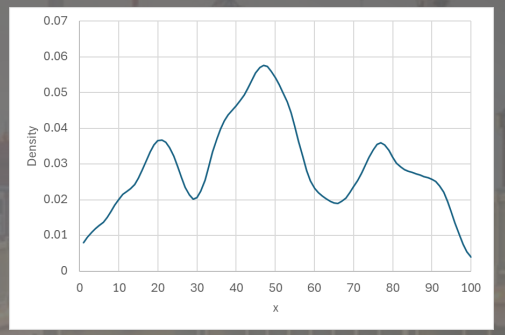
IDENTIFICATION AND EXTRACTION OF INPUT PARAMETERS FROM IMAGES

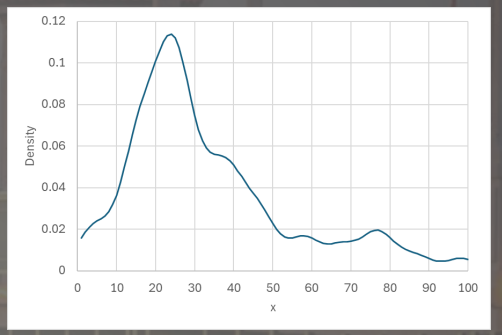




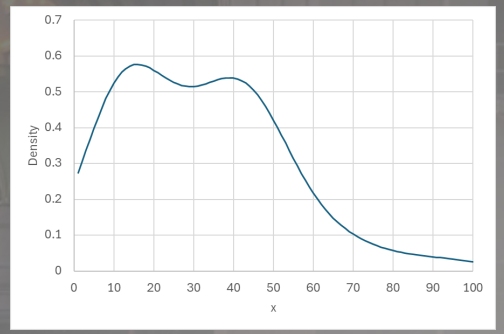
Average PDF



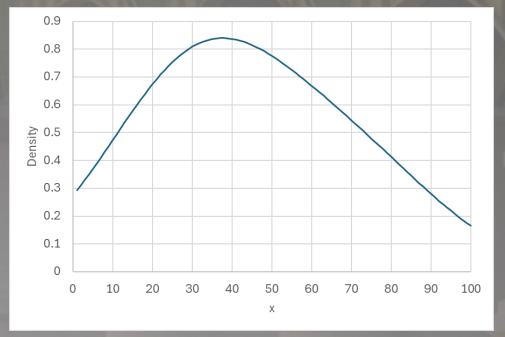
Standard Deviation PDF



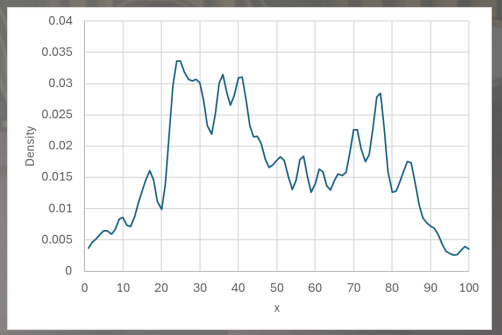
RMS PDF



Kurtosis PDF



Skewness PDF



IQR PDF

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BUILDING RFC ESTIMATORS

Typical Confusion Matrix for Current Model

Predicted / Actual	None	Low	Med	Sev
None	260	7	0	0
Low	15	270	53	1
Med	3	49	230	3
Sev	0	8	20	78

Typical Classification Report for Current Model

Category	Precision	Recall	F1-score	Support
None	0.94	0.97	0.95	267
Low	0.81	0.80	0.80	339
Med	0.76	0.81	0.78	285
Sev	0.95	0.74	0.83	106
Accuracy			0.84	997
Macro Avg.	0.86	0.83	0.84	997
Weighted Avg.	0.84	0.84	0.84	997

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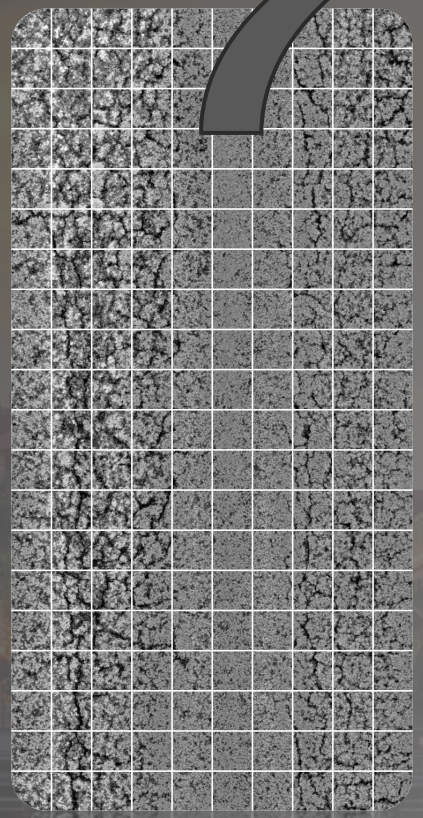
USE THE RANDOM FOREST CLASSIFIER TO CLASSIFY THE PRODUCTION DATA



None

Low

Medium

Severe

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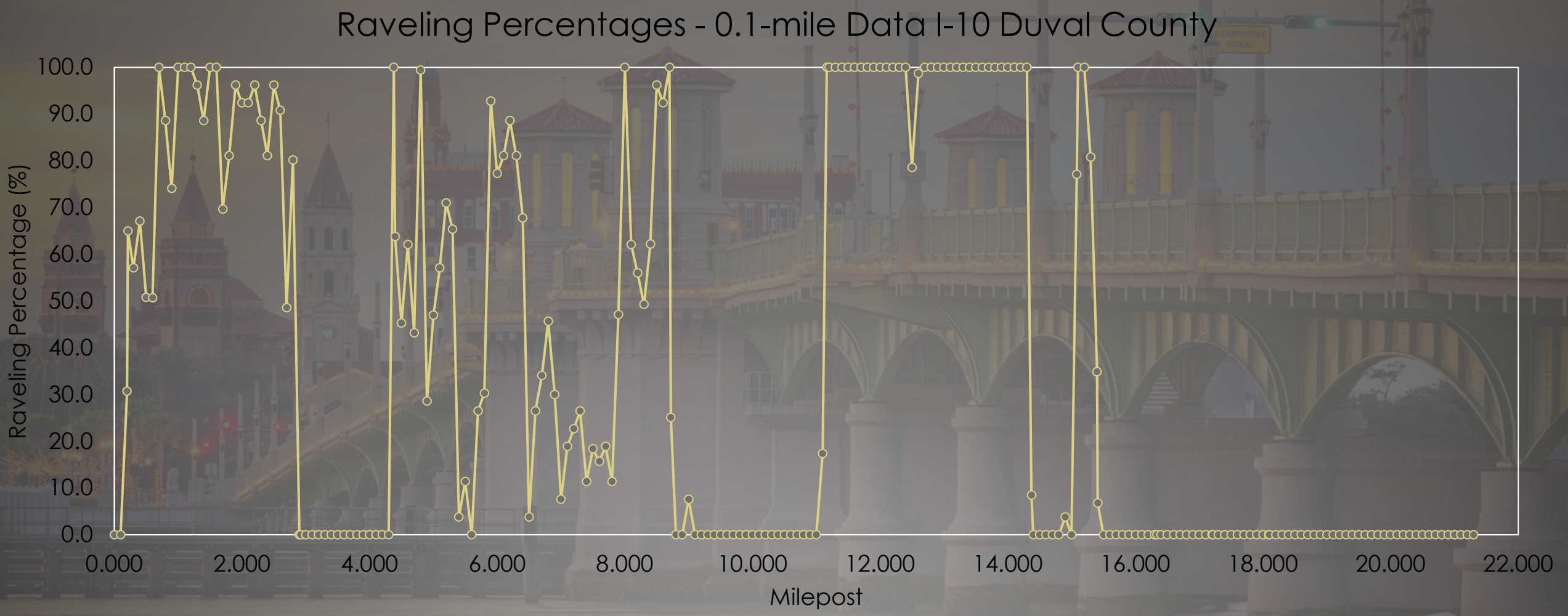
OUTPUT THE CLASSIFICATION TO THE SQL DATABASE AND .CSV FILE



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RANDOM FOREST ALGORITHM

Building and Training of the Model

Categorizing Images

Manual ratings of training set images

Define the random forest model (hyperparameters)

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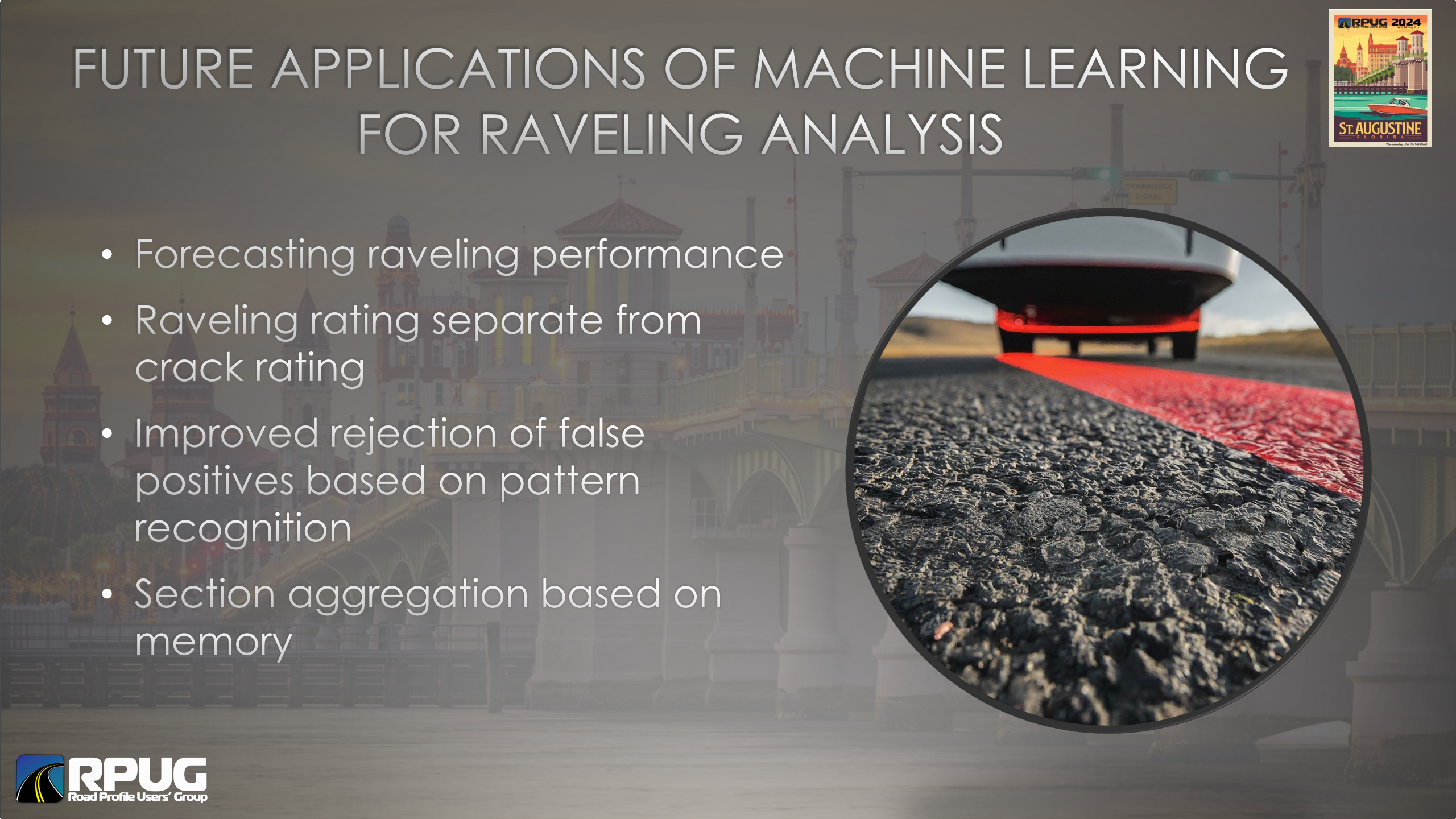
FUTURE APPLICATIONS OF MACHINE LEARNING FOR RAVELING ANALYSIS



- Forecasting raveling performance
- Raveling rating separate from crack rating
- Improved rejection of false positives based on pattern recognition
- Section aggregation based on memory

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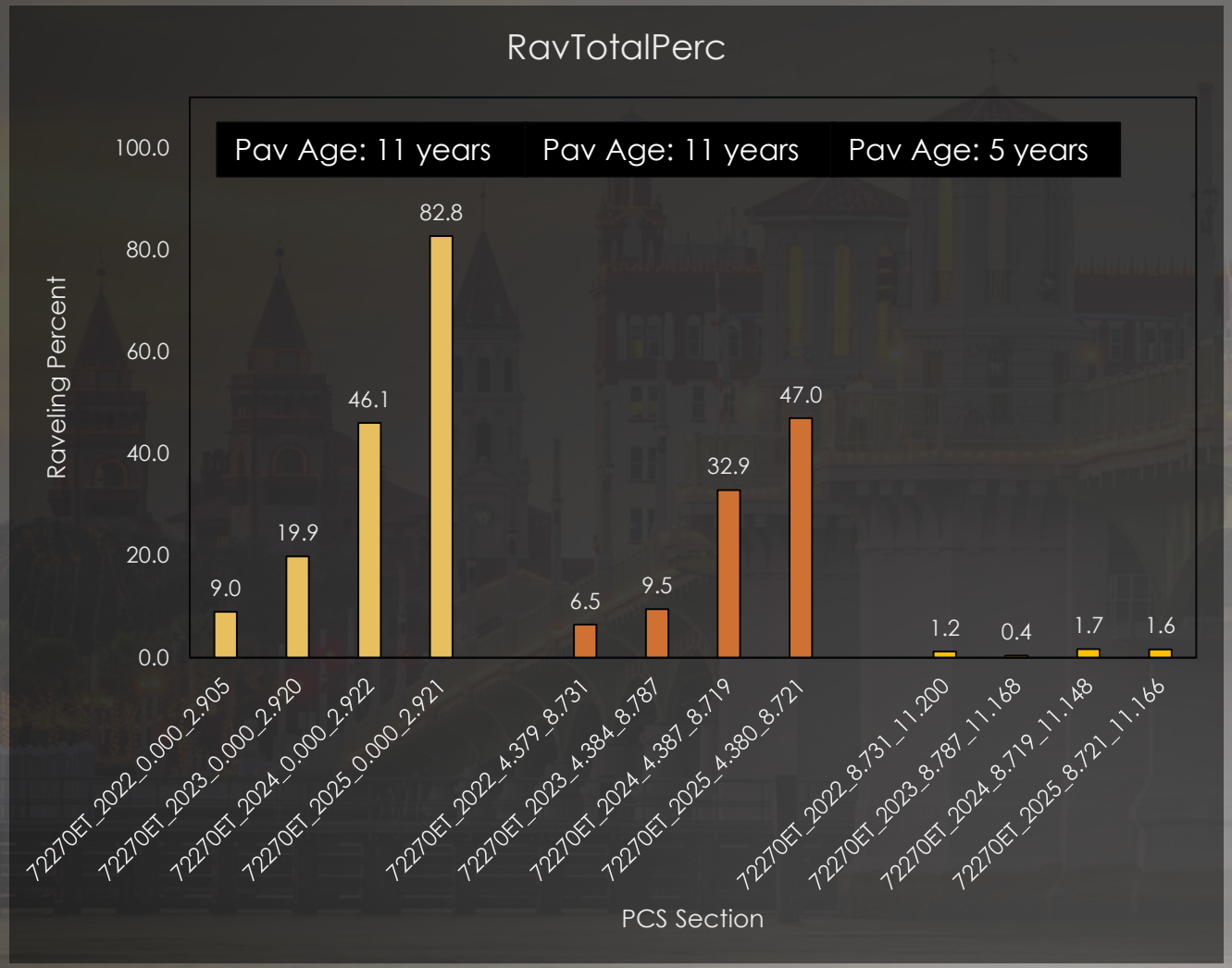
FORECASTING RAVELING PERFORMANCE



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RAV RATING SEPARATE FROM CRACK RATING

- Cracking Model
  - OGFC
    - CW Deduct
      - Crack Deduct
        - X_1 = CW Crack %
        - X_2 = Avg. Crack width (in)
        - $aX_1^{(b+(0.1X_2-0.025))}$
      - Rav Deduct
        - r_1 = Low Rav %
        - r_2 = Mod. Rav %
        - r_3 = Sev. Rav %
        - $c(d \cdot r_1+e \cdot r_2+f \cdot r_3)^g$
      - CW deduct [0,7]
    - CO Deduct
      - X_1 = CO Crack %
      - X_2 = Avg. Crack width (in)
      - $aX_1^{(b+(0.1X_2-0.025))}$
      - CO Deduct [0,3]
    - **CRACK RATING = 10 – (CW + CO)**
  - DGFC
    - CW Deduct
      - X_1 = CW Crack %
      - X_2 = Avg. Crack width (in)
      - $aX_1^{(b+(0.1X_2-0.025))}$
      - CW Deduct [0,7]
    - CO Deduct
      - X_1 = CO Crack %
      - X_2 = Avg. Crack width (in)
      - $aX_1^{(b+(0.1X_2-0.025))}$
      - CO Deduct [0,3]
    - **CRACK RATING = 10 – (CW + CO)**

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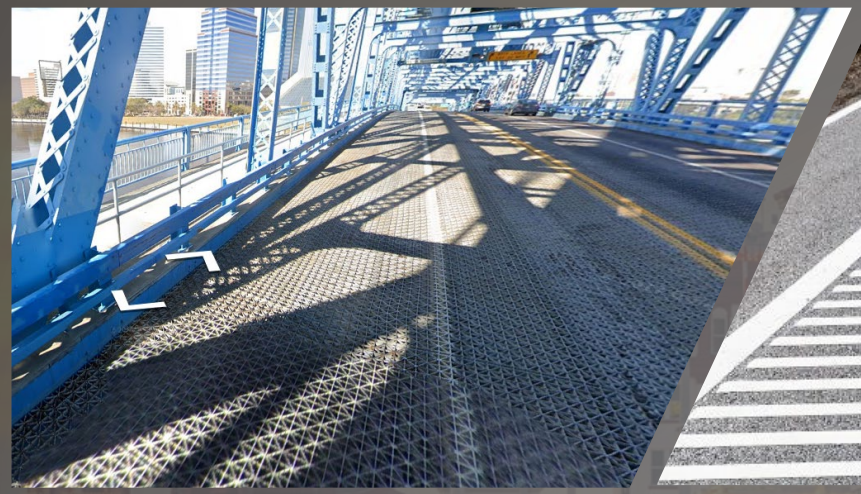
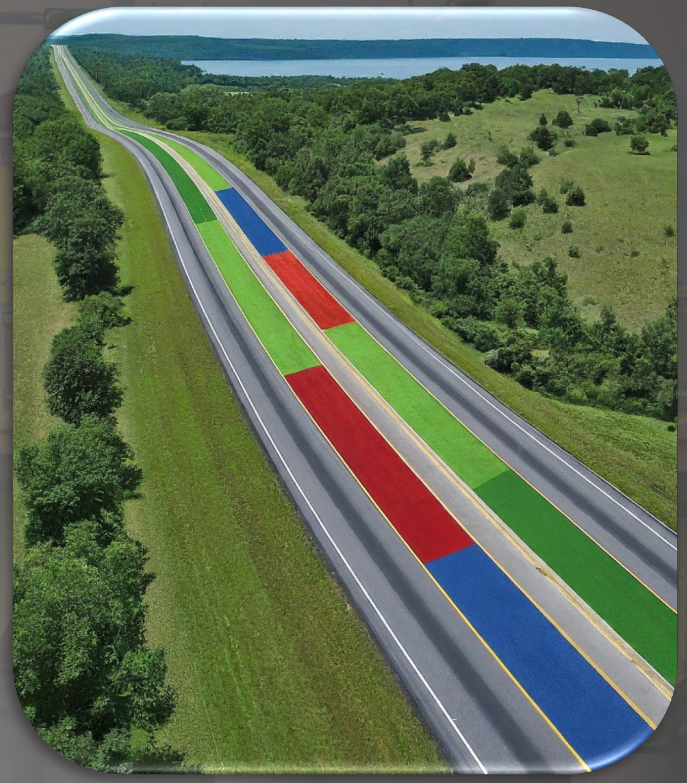
IMPROVED REJECTION OF FALSE POSITIVES BASED ON PATTERN RECOGNITION





Section aggregation based on memory

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QUESTIONS SECTION

THANK YOU!