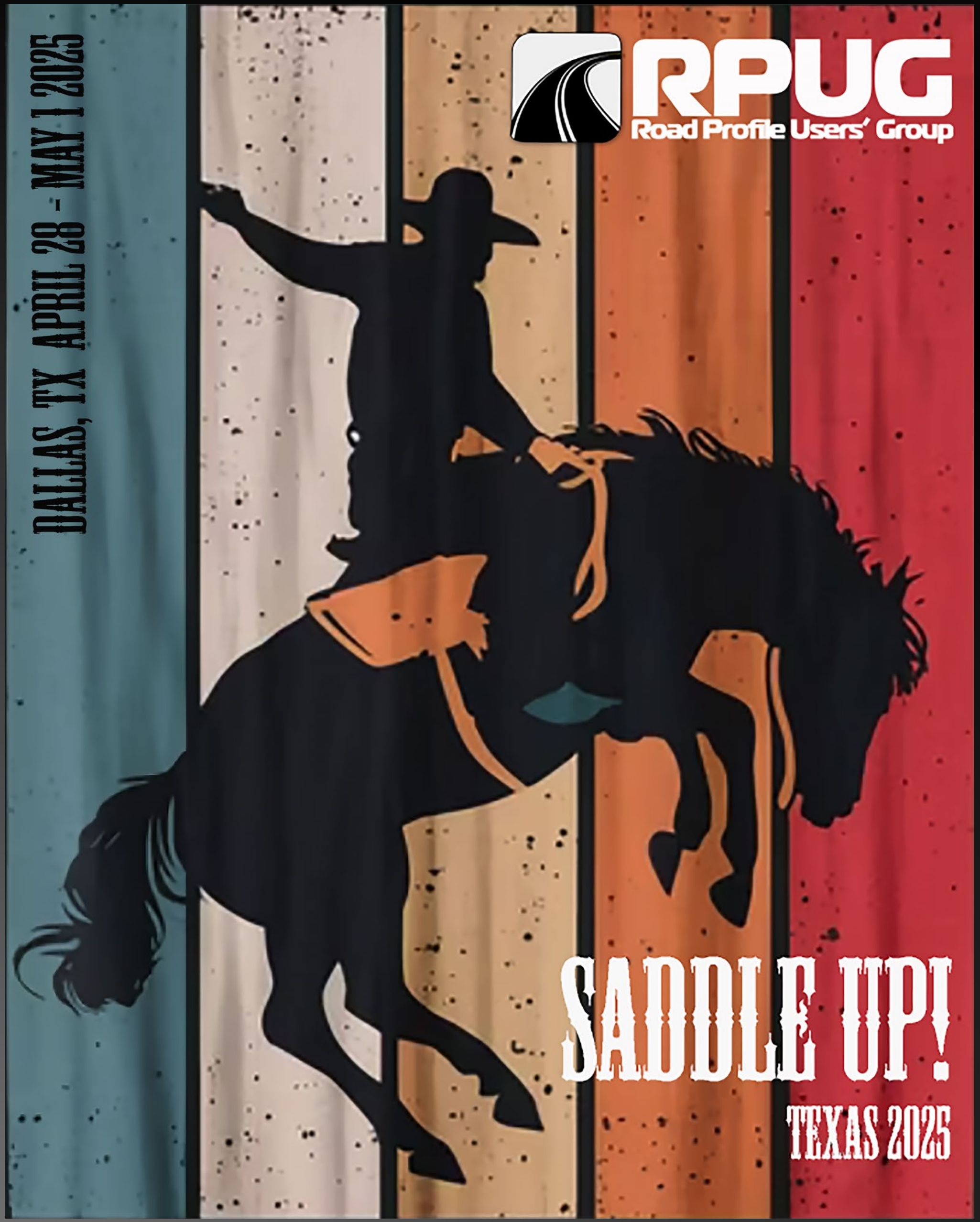

Automated And Interpretable Classification Of Jointed Plain Concrete Pavement (JPCP) Slab State Using Crack Vector Model (CVM)

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APRIL, 2025

RPUG
Road Profile Users' Group

JPCP Slab State Classification

- Classifying slab states based on cracking patterns, such as longitudinal, transverse, corner cracking, or a combination of these (i.e., shattered), is critical for determining the condition of Jointed Plain Concrete Pavements (JPCP).

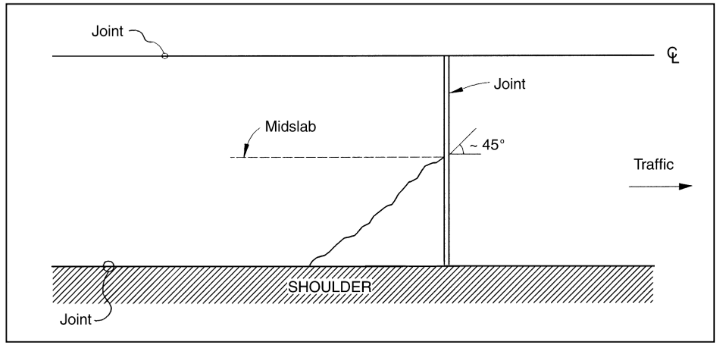


FIGURE 48
Distress Type JCP 1—Corner Breaks.

FIGURE 49
Distress Type JCP 1—Low Severity Corner Break.

FIGURE 50
Distress Type JCP 1—Moderate Severity Corner Break.

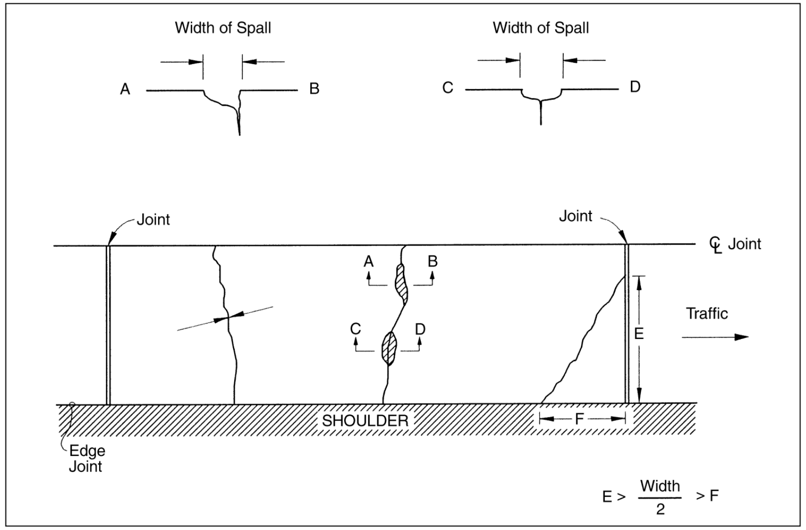


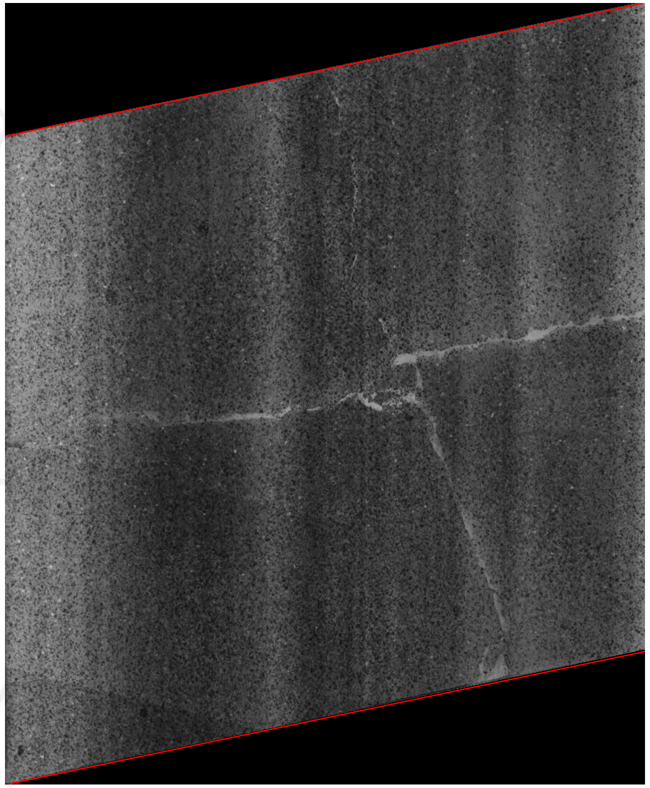
FIGURE 58
Distress Type JCP 4—Transverse Cracking.

FIGURE 57
Distress Type JCP 3—High Severity Longitudinal Cracking.

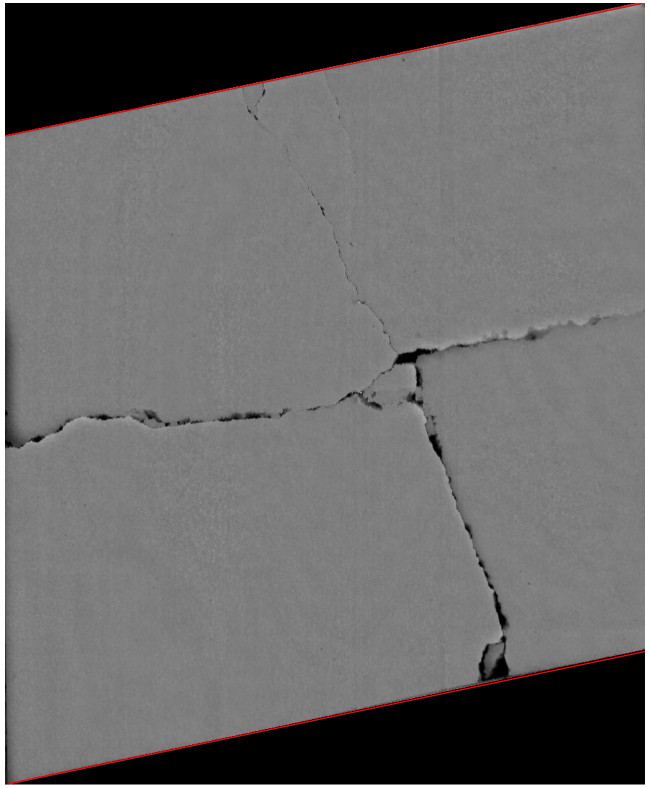
Figures captured from the LTPP manual: Miller, J. S., & Bellinger, W. Y. (2003). *Distress identification manual for the long-term pavement performance program.*

Availability of Pavement Images and Crack Maps

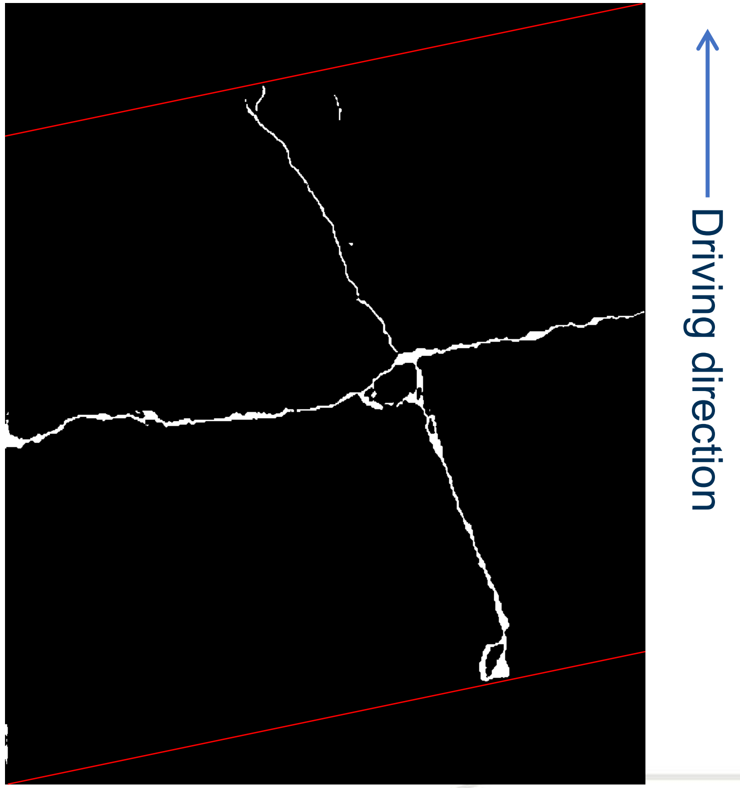
- With the availability of crack maps derived from high-resolution 3D pavement surface images, there is a significant opportunity to automate the classification of JPCP slab states based on cracking.



(a) Intensity Image



(b) Range Image

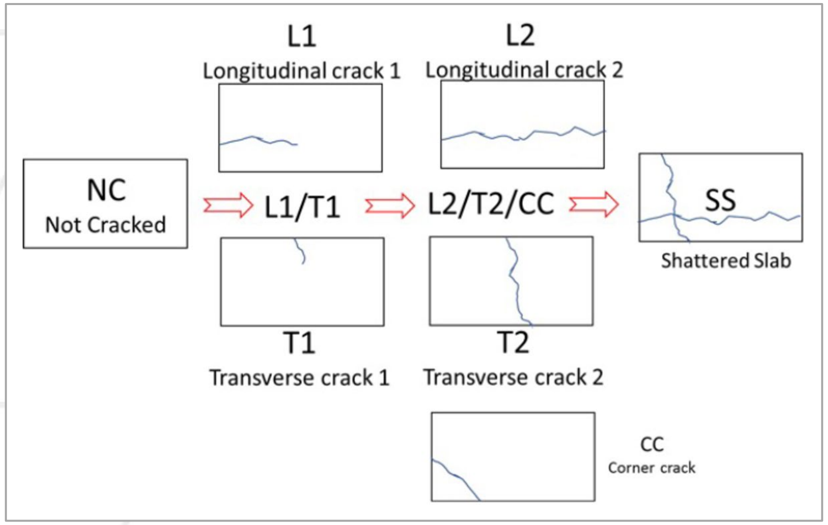


(c) Crack Maps

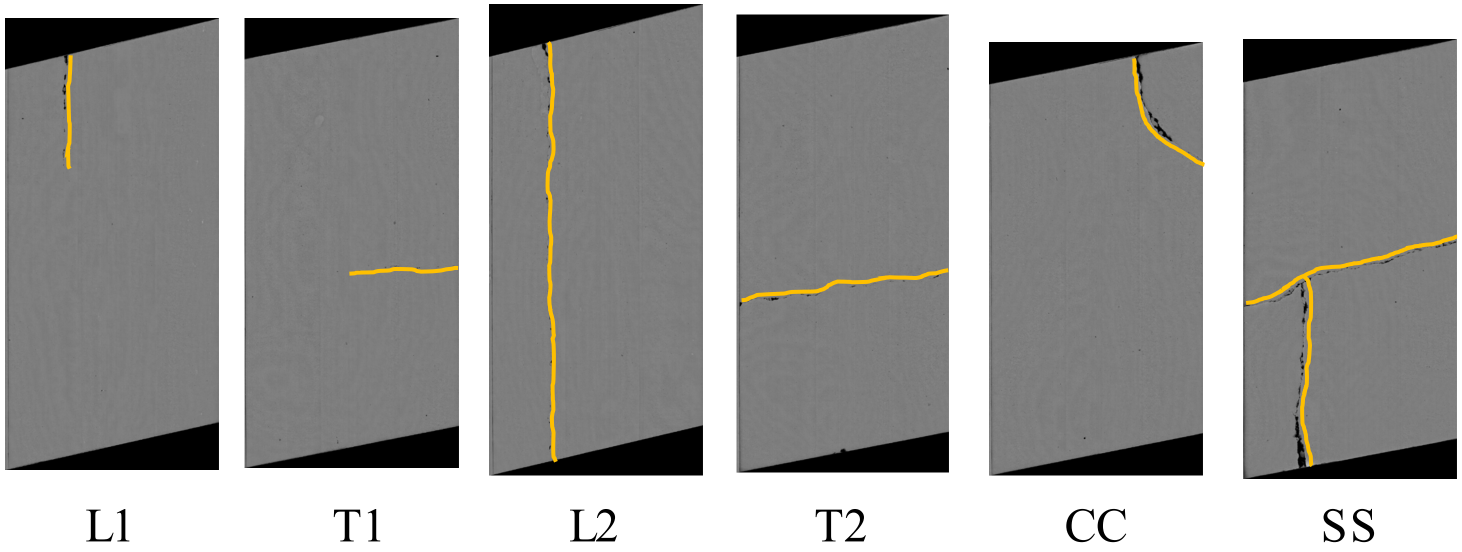
Data was collected by the Georgia Tech Sensing Vehicle (GTSV) on I-16 Westbound (MP 22 to 12) in Georgia. This JPCP is designed with a skew.

JPCP Slab State Classification: New Definitions

- An LTPP revised slab-classification has been proposed and used to categorize typical JPCP cracking deterioration, which can assist in monitoring and treatment decision-making (Geary, 2019).



Slab State Definition Based on Cracking Pattern (Geary, 2019)



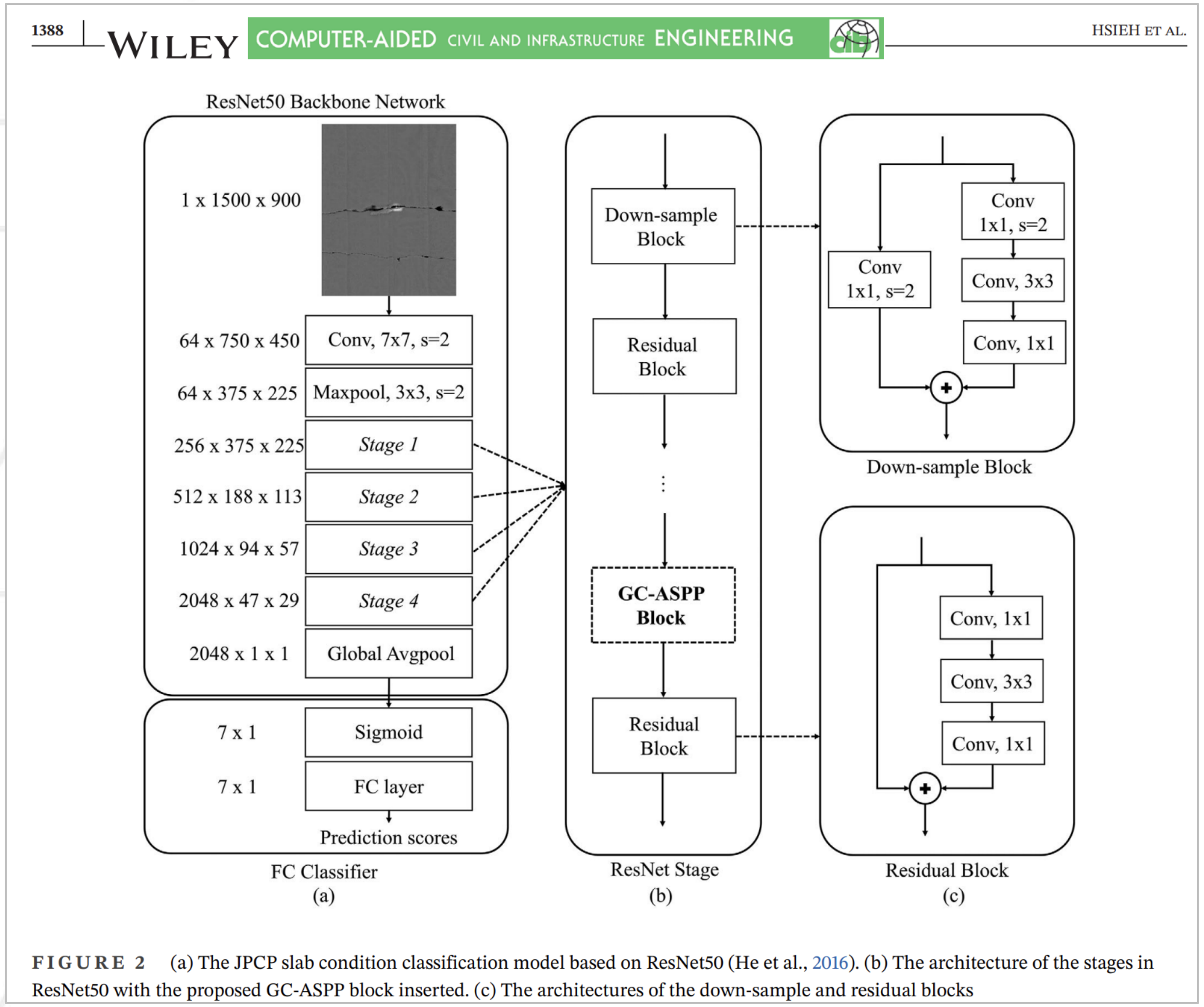
Sample Slab States (Geary, 2019; Salameh, 2025)

- This JPCP slab classification is being incorporated into NCHRP 01-57B.
- There is a need for an automated JPCP slab classification method.

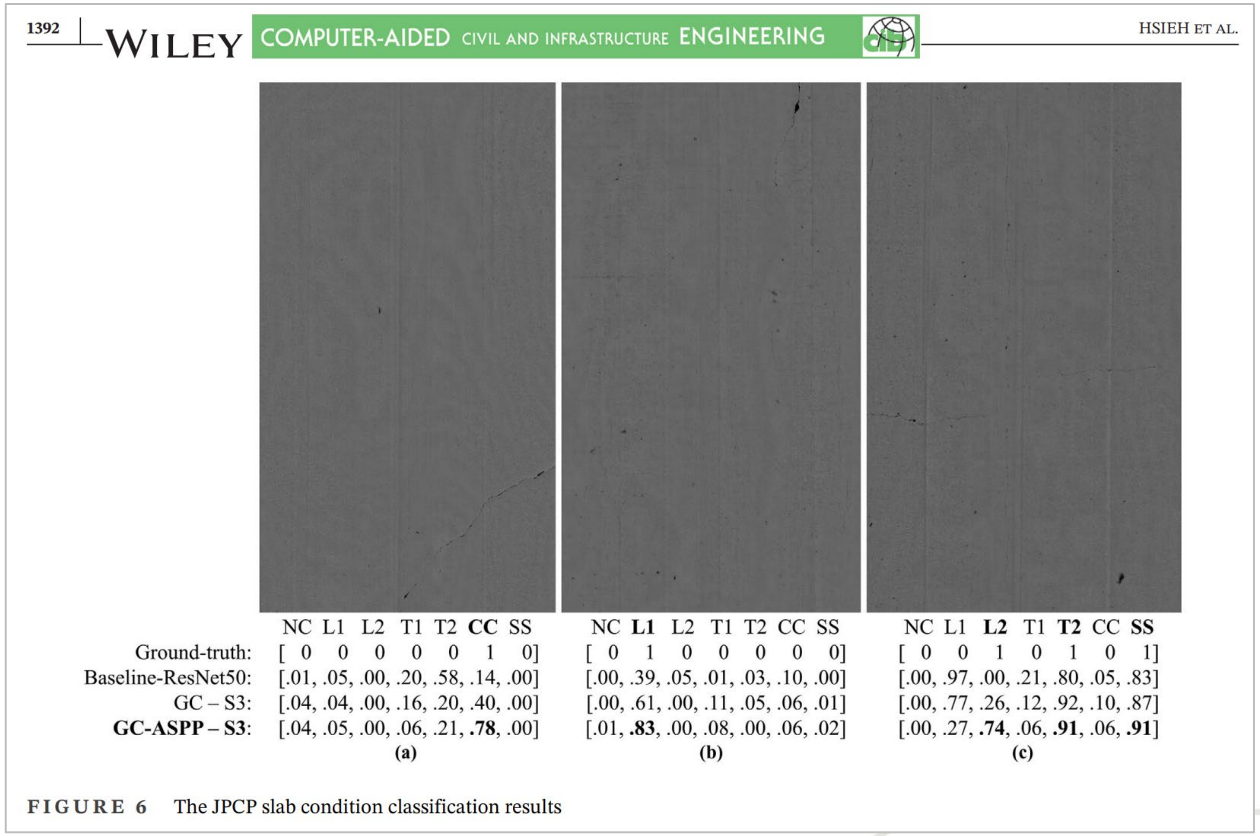
Geary, G. M. (2019). A spatial and temporal 3D slab-based methodology for optimized concrete pavement asset management.
Salameh, R. (2025). Optimizing Project-level Pavement Asset Management: Predictive and Precision-based Maintenance with 3D Pavement Surface Data.

Previous Work: DL-based JPCP Slab Classification

- A DL-based model was developed to conduct end-to-end JPCP slab classification; however, this method is difficult to interpret and implement (Hsieh et al., 2021).



* The accuracy of this DL-based model is around 85%



Can we use crack maps to classify slabs?

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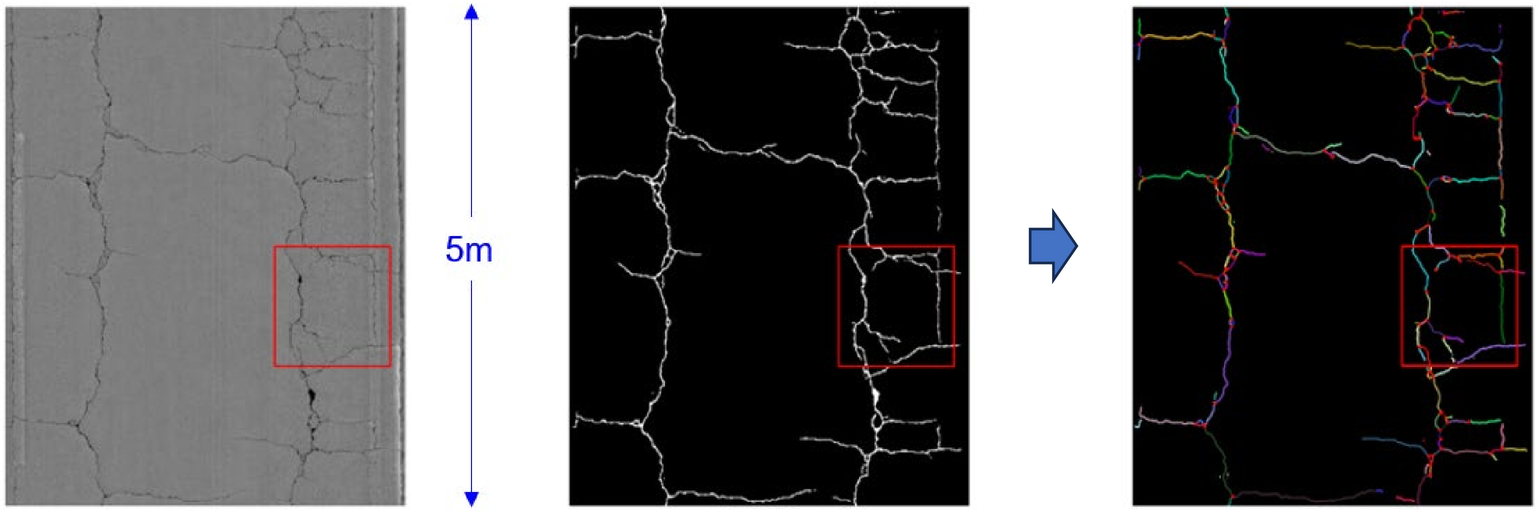
Hsieh, Y. A., Yang, Z., & James Tsai, Y. C. (2021). Convolutional neural network for automated classification of jointed plain concrete pavement conditions. *Computer-Aided Civil and Infrastructure Engineering*, *36*(11), 1382-1397.

Representing Crack Maps Using Crack Vector Model (CVM)



(a) Range Image

(b) Detected Crack Maps (Different vendors have different methods)

(c) Crack Vector Model (CVM)

1) Higher Level Cracking Definitions (Grid-based)

2) HPMS Reporting
E.g., % Wheelpath fatigue cracking for flexible pavements

3) State Agencies' Protocols
SHA's distress protocol and treatment decision-trees

4) Cracking Data Quality Assessment Using Crack Maps

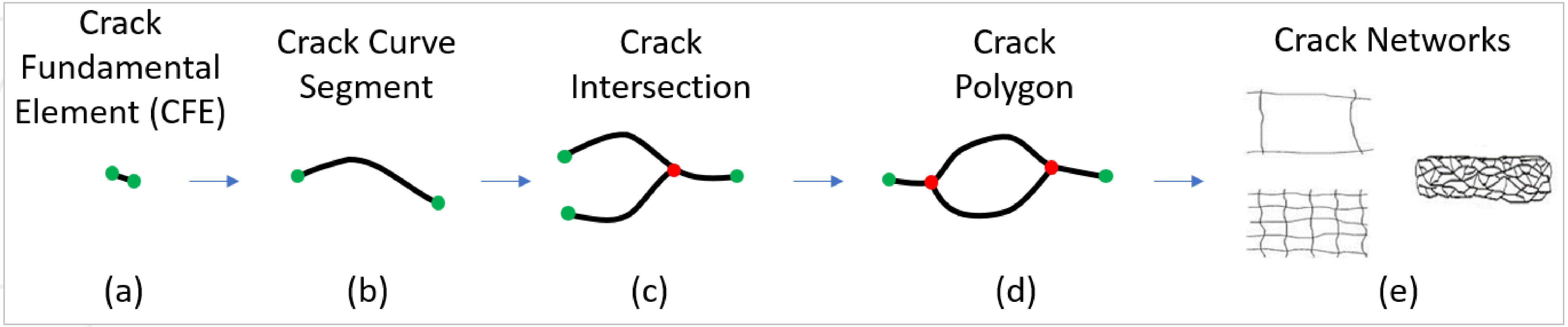
* The new cracking definitions using CVM are expected to be fundamental and flexible enough to support different applications.

The Crack Vector Model (CVM) is a method that implements the concept of Crack Fundamental Elements (CFEs), proposed by Dr. Tsai in 2014 (Tsai et al., 2014). This method was also introduced for developing a standardized cracking definition in **NCHRP Project 01-57B**.

Tsai, Y.-C., Jiang, C., & Huang, Y. (2014). Multiscale crack fundamental element model for real-world pavement crack classification. *Journal of Computing in Civil Engineering*, *28*(4), 04014012.

The Concept of Crack Fundamental Element (CFE)

- Core ideas of the CFE concept:
  1. Using fundamental geometry elements, like node and link, to represent crack geometry.
  2. Flexible enough to support different cracking definitions and protocols.
  3. Similar to roadway networks; existing GIS knowledge is leveraged.

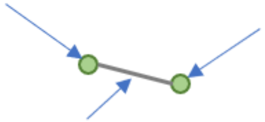
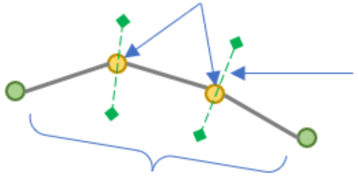
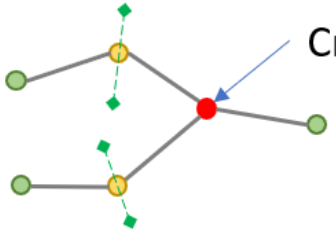
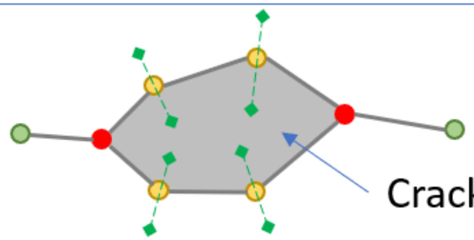


- The Crack Vector Model (CVM) is then developed to implement the concept of the CFE (Yang, 2024; Yang et. al., 2025).

*Similar Terminologies have been defined in AASHTO R85 (e.g., crack, crack terminus, crack position, etc.)

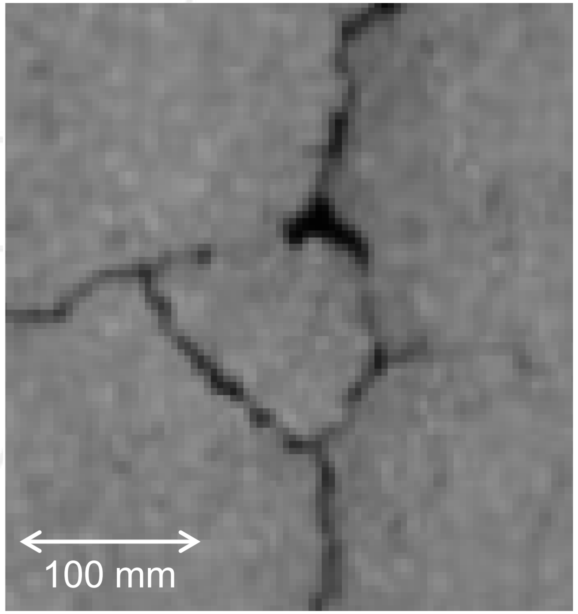
Yang, Z., Fung, J., Ho, H., & Tsai, Y.-C. (2025). A Predictive and Precision Pavement Maintenance Methodology Utilizing Multi-Temporal Pavement Images. *Transportation Research Record (under review)*.
Yang, Z. (2024). CRACK PROPAGATION ANALYSIS USING PAVEMENT IMAGE REGISTRATION AND CRACK VECTOR MODEL FOR PREDICTIVE AND PRECISION PAVEMENT MAINTENANCE. School of Civil and Environmental Engineering, Georgia Institute of Technology. **Doctor of Philosophy**.

Definition of Crack Vector Model (CVM)

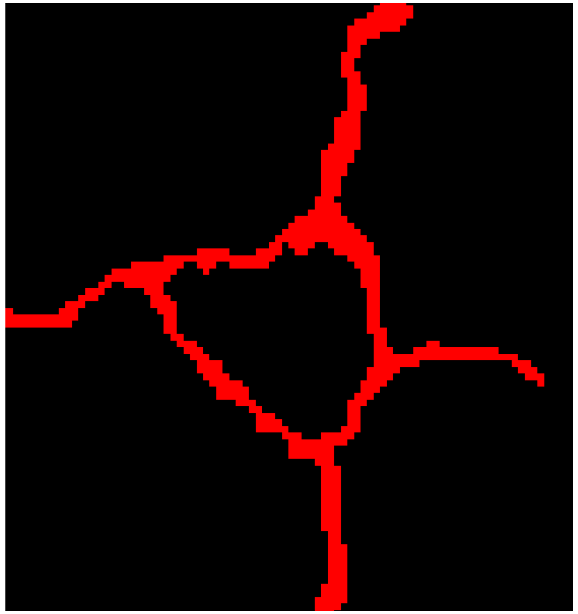
Level	Level description	Actual crack shape	Geometrical representations	New properties at the level (compared to prior level)
1	A single piece of **crack fundamental element** (CFE)			1. Length of the CFE 2. Orientation of the CFE 3. Number of end points
2	Connected CFEs (formed a **crack curve segment**)			1. Length of the crack branch 2. Crack width at each vertex 3. Average width of the branch
3	Connected CFEs (formed a **crack intersection**)			1. Number of crack intersections 2. Number of crack branches
4	Connected CFEs (formed a **crack polygon**)			1. Number of crack polygons 2. Size of each polygon

Procedures to Establish CVM from Range Image

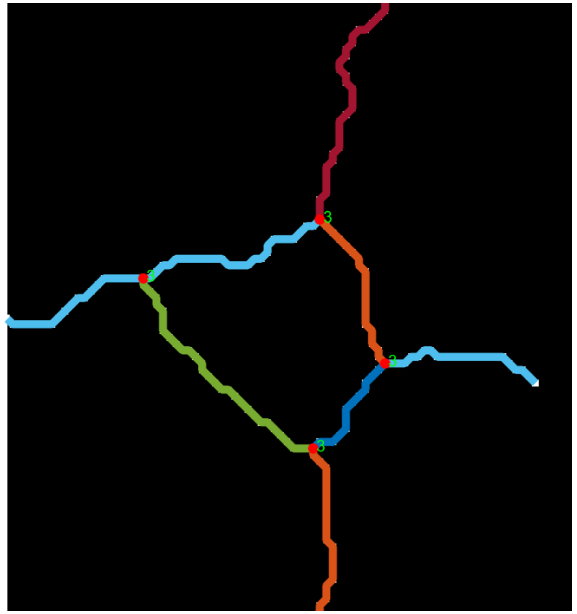
- This is an illustration of CVM using Asphalt pavement images.



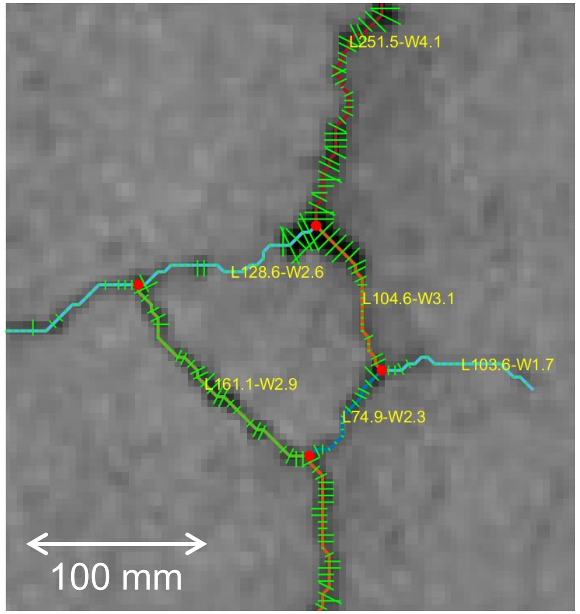
(a) Range image



(b) Crack Segmentation



(c) Crack Skeleton



(d) Crack Vector Model

(a) → (b): Cracking segmentation (pixel-level crack map detection)
(b) → (c): Using morphological operations to extract the crack skeleton, then identify the cracking intersection and individual crack links.
(c) → (d): Overlay with range image, the cracking width can be measured at each cracking vertices.

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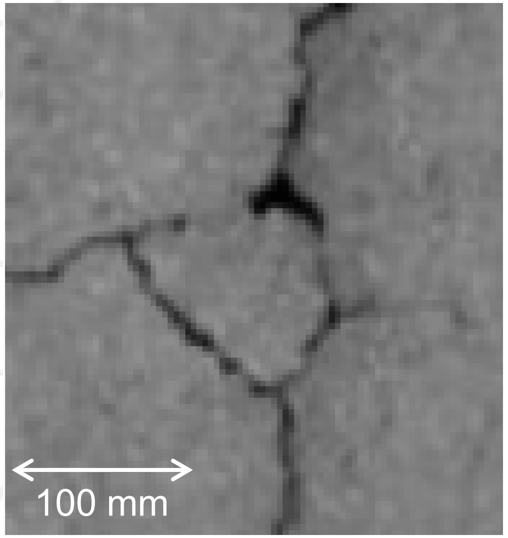
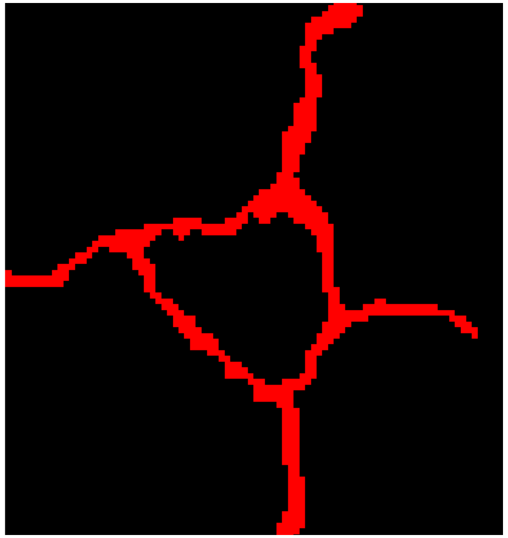
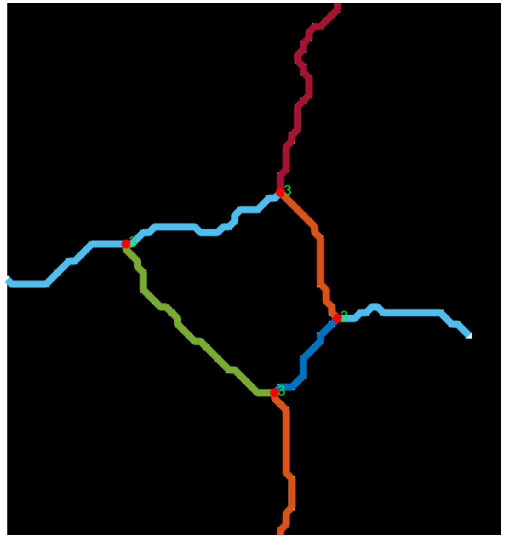
Analogy Between CVM and GIS (geographic information system)



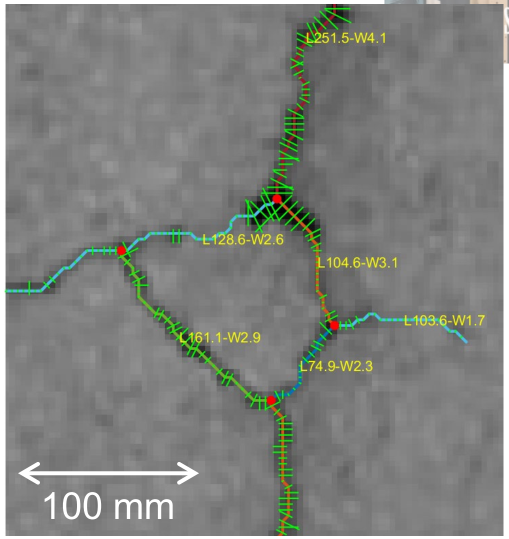
(a) Range image



(b) Crack Segmentation

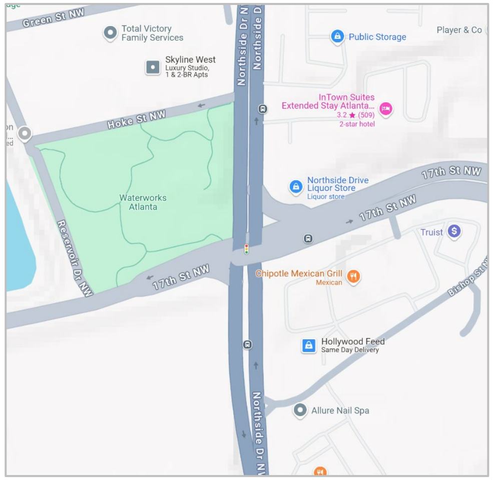


(c) Crack Skeleton

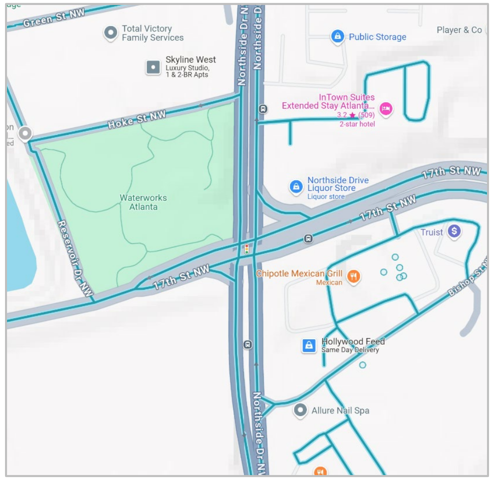


(d) Crack Vector Model

(e) Satellite Image



(f) Map Segmentation



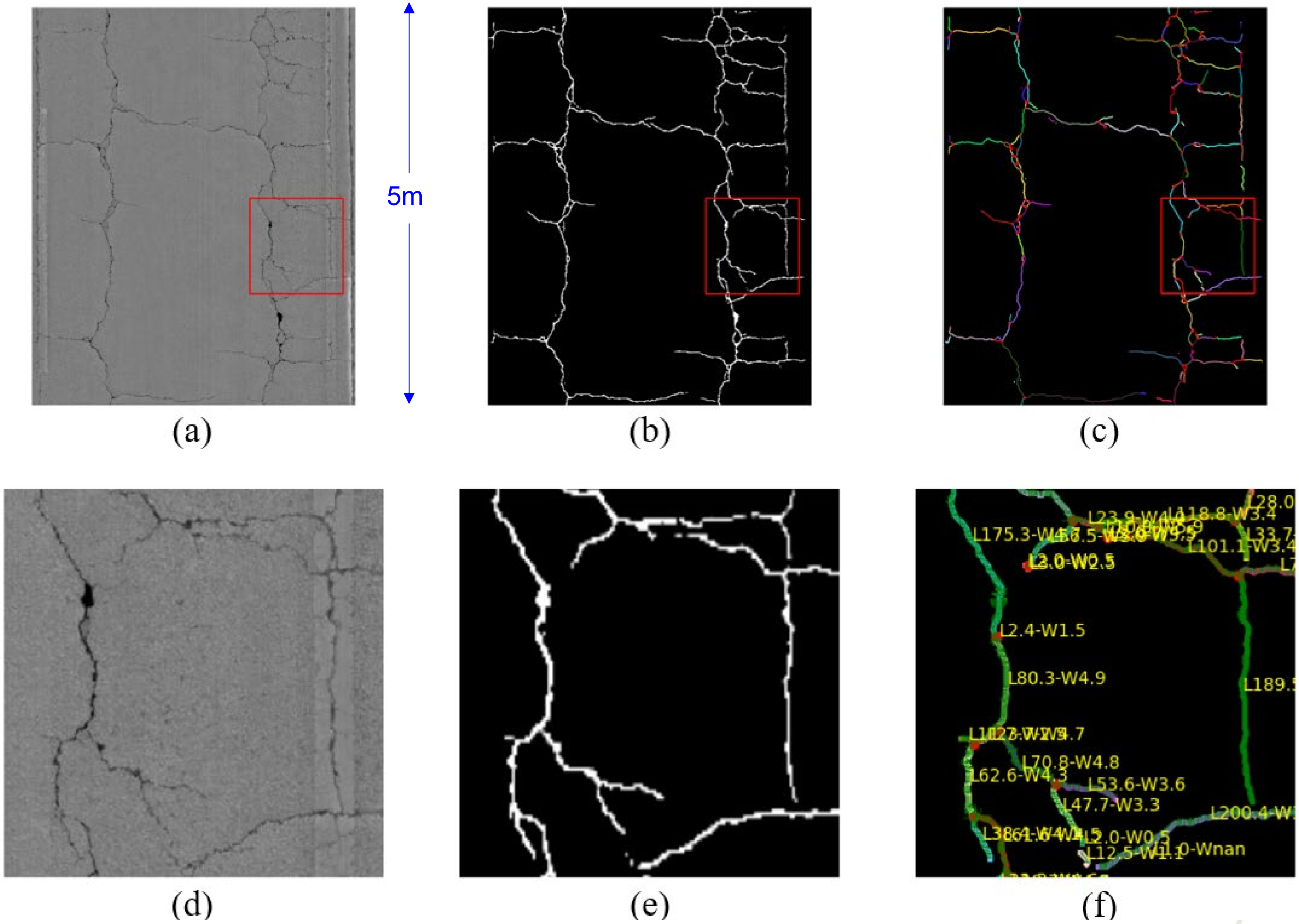
(g) Road Network

(h) Traffic Information

*Map figures were captured from Google Maps.

Comparison of Range, Segmentation, and CVM Data

~2 MB



~200 KB

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Standard Data Format for CVM Storage

GeoJSON

```
{
  "type": "FeatureCollection",
  "features": [
    {
      "type": "Feature",
      "geometry": {
        "type": "LineString",
        "coordinates": [[30, 10], [10, 30], [40, 40]]
      },
      "properties": {
        "crack branch id": "1",
        "width": [0, 2.5, 0]
      }
    },
    {
      "type": "Feature",
      "geometry": {
        "type": "LineString",
        "coordinates": [[40, 10], [20, 20], [30, 30], [35, 35], [50, 50]]
      },
      "properties": {
        "crack branch id": "2",
        "width": [0, 1, 2.5, 2, 0]
      }
    }
    // Additional crack branches can be added here in the same format.
  ]
}
```

Crack Branch 1

Crack Branch 2

A standard, simple, and universe data format supports large scale implemented in the future.

GeoDataframe

	geometry	crack branch id	width
0	LINESTRING (30 10, 10 30, 40 40)	1	[0, 2.5, 0]
1	LINESTRING (40 10, 20 20, 30 30, 35 35, 50 50)	2	[0, 1, 2.5, 2, 0]
...	...	...	...

Note: Other crack properties (e.g., crack length, width, number of intersections, number of branches) can be computed from this simple data storage format, using simple query functions.

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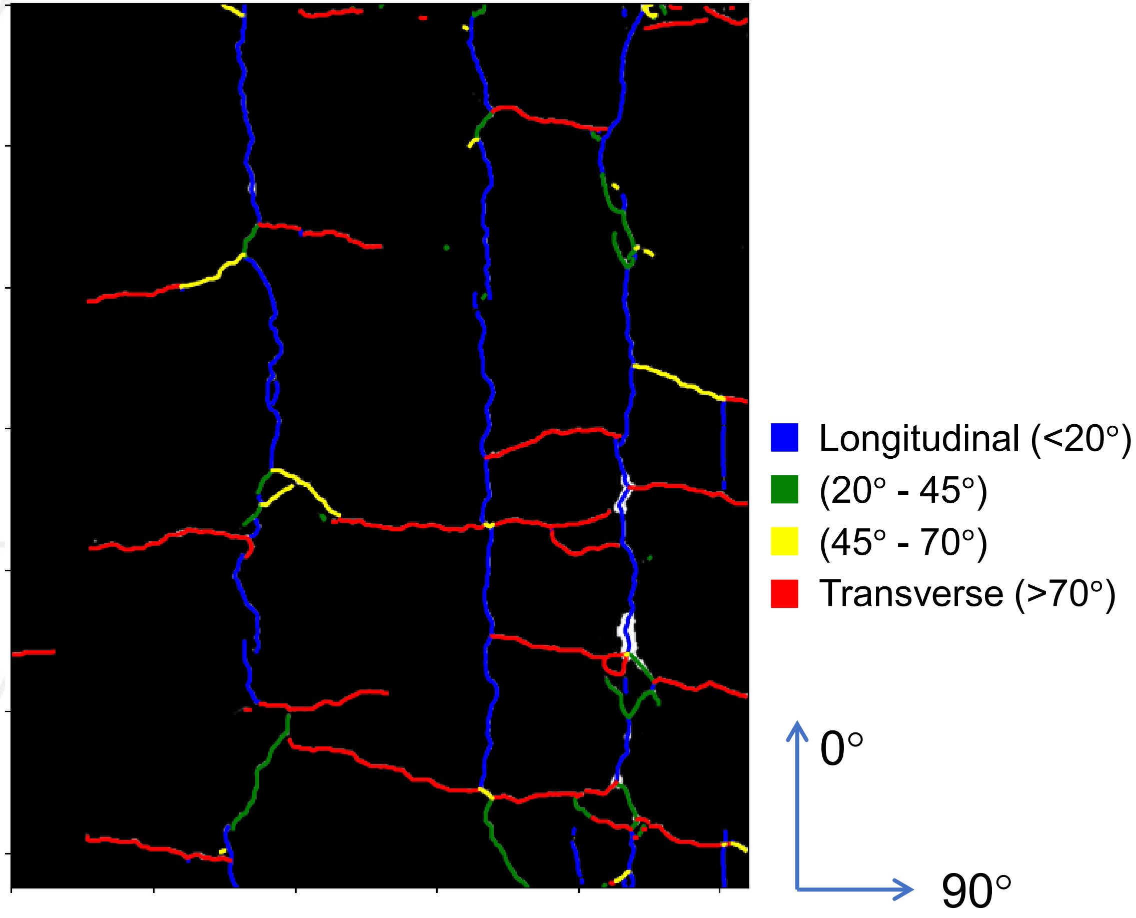
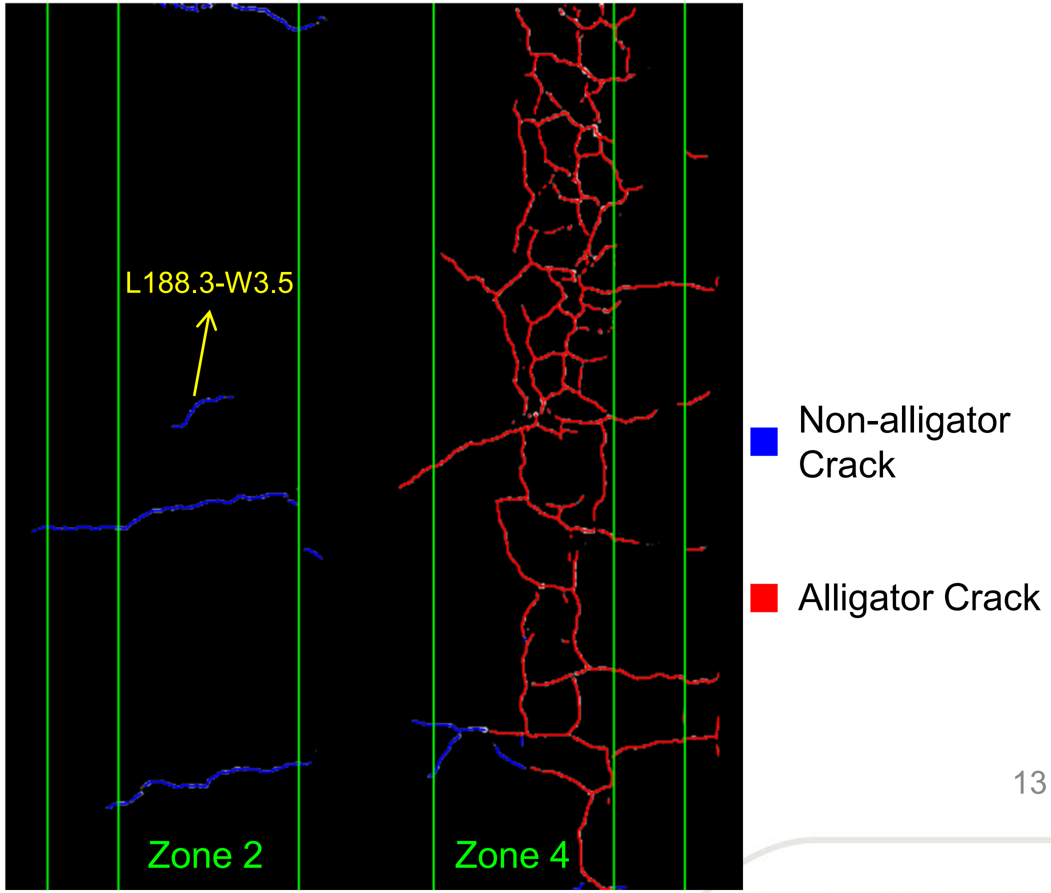
Link-wise Cracking Classification and Attributes Computation Using CVM

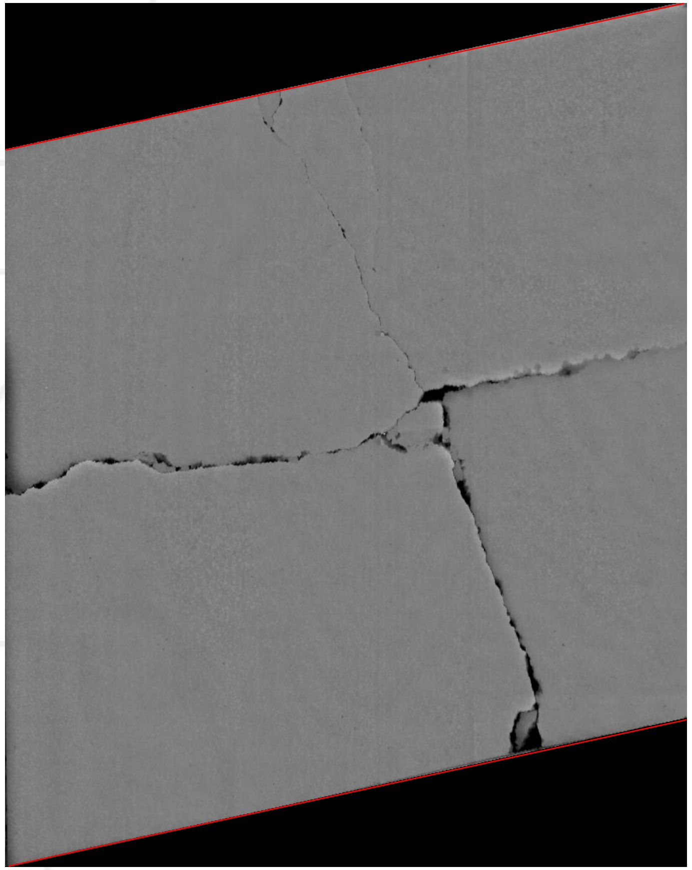
- Using CVM, each individual crack link can be categorized based on cracking width, orientation, location, and density. Their properties can also be computed.



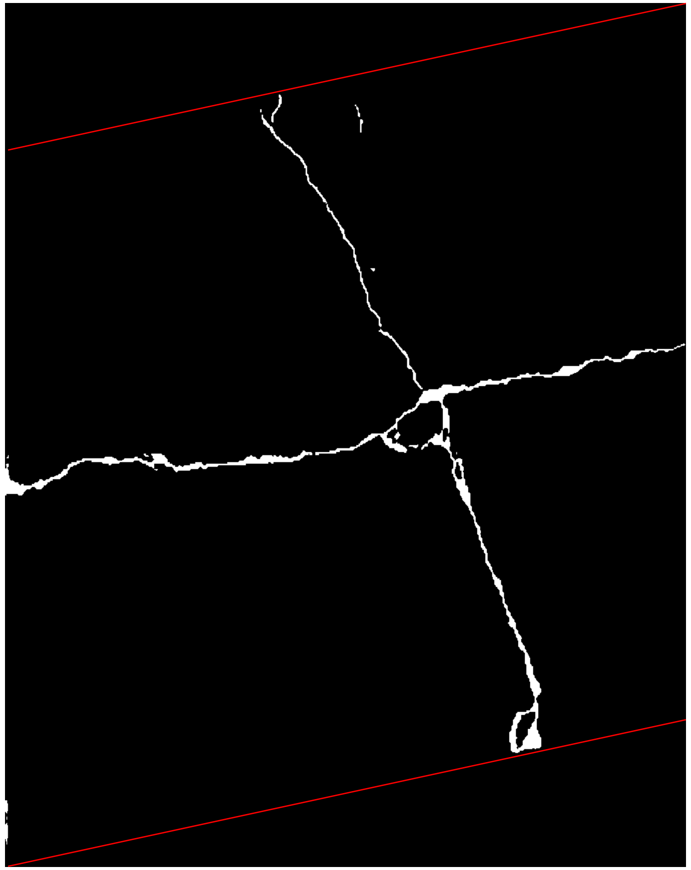


*A simple model based on cracking density was used to identify alligator cracks in this study. Other alternative methods using ML or DL are available.

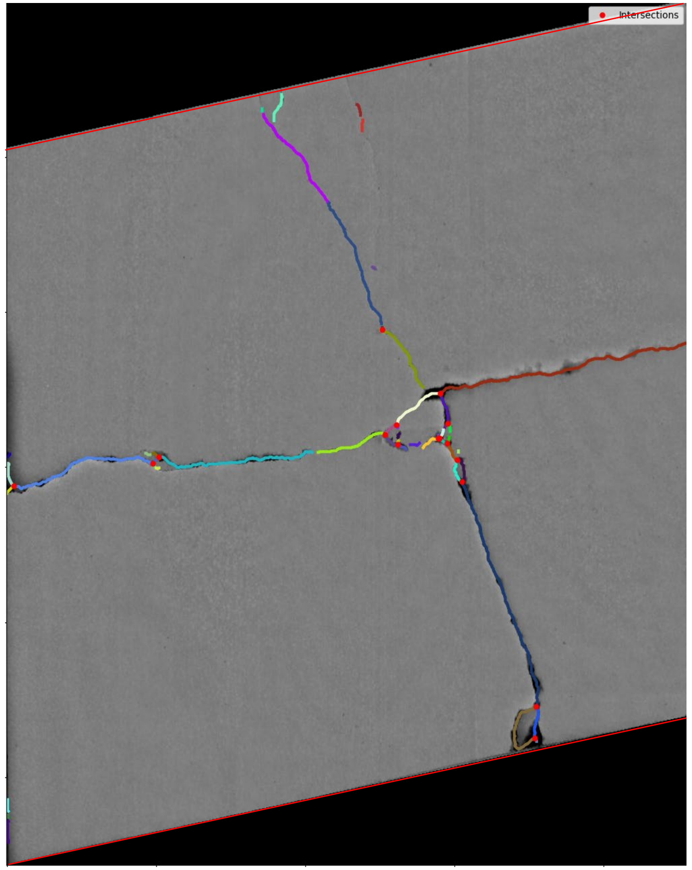
Crack Vector Model (CVM) Implementation on JPCP



(a) Range Image



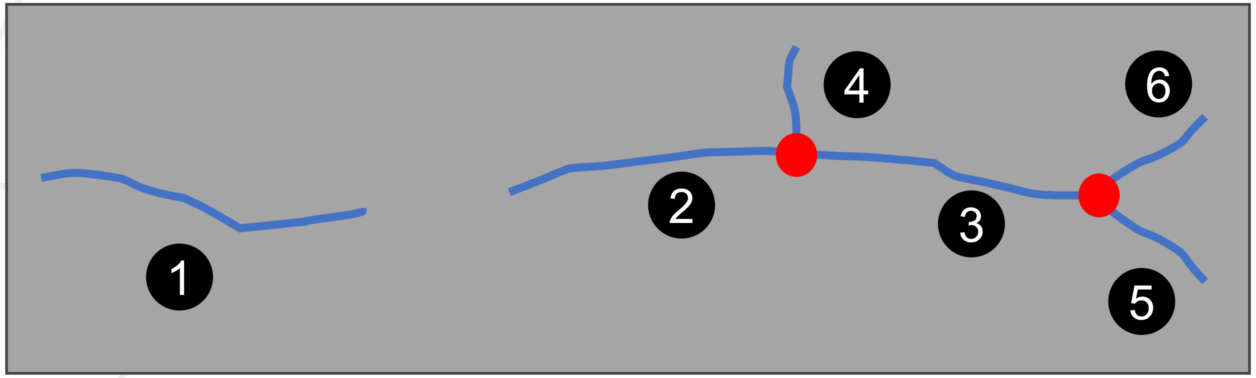
(b) Crack Maps



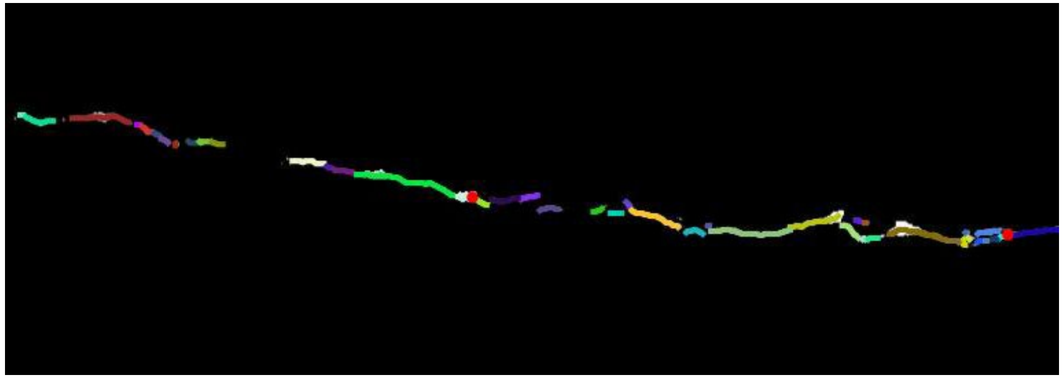
(c) Crack Vector Model

Challenges of Using Crack Maps for Slab Classification

- Crack bifurcation and discontinuity may cause misclassification
  1) The crack map can be discontinuous (even the crack in the real world is continuous), making the crack link shorter than 12".
  2) Crack bifurcated, causing the crack link to be too short to cross different zones.



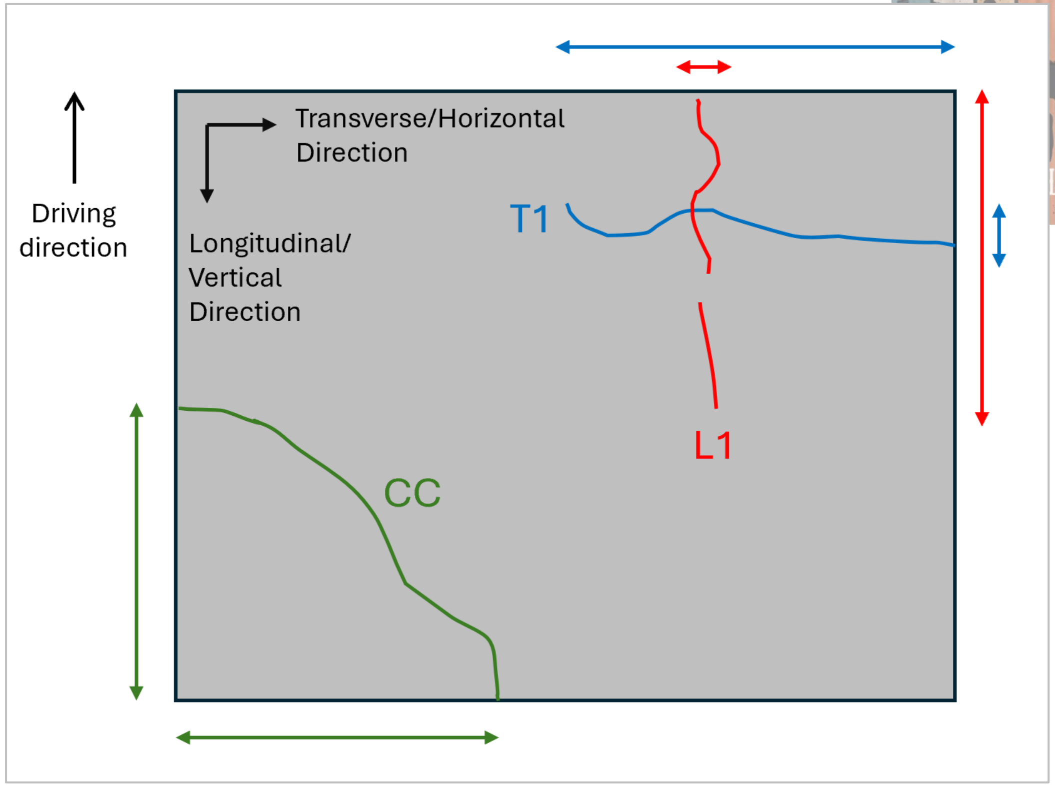
(a) Illustration of the challenges



(b) A sample of issues on CVM

Proposed Methodology

- A multi-dimensional cracking extent projection method is introduced to extract geometric features from crack maps. Then, a decision tree is used to classify slab states.
  - Step 1: Classify crack types according to orientation
    - Longitudinal: 0° <= Orientation < 20°
    - Transverse: 70° < Orientation <= 90°
    - Other: 20° <= Orientation <= 70°
  - Step 2: Measure and represent crack extent in both directions (vertical and horizontal).
    - Small gaps are filled (< 80mm).
  - Step 3: Extract features that describe the geometry of the crack extent.
    - E.g., length of crack extents in different directions.
  - Step 4: Slab state classification using decision tree models.



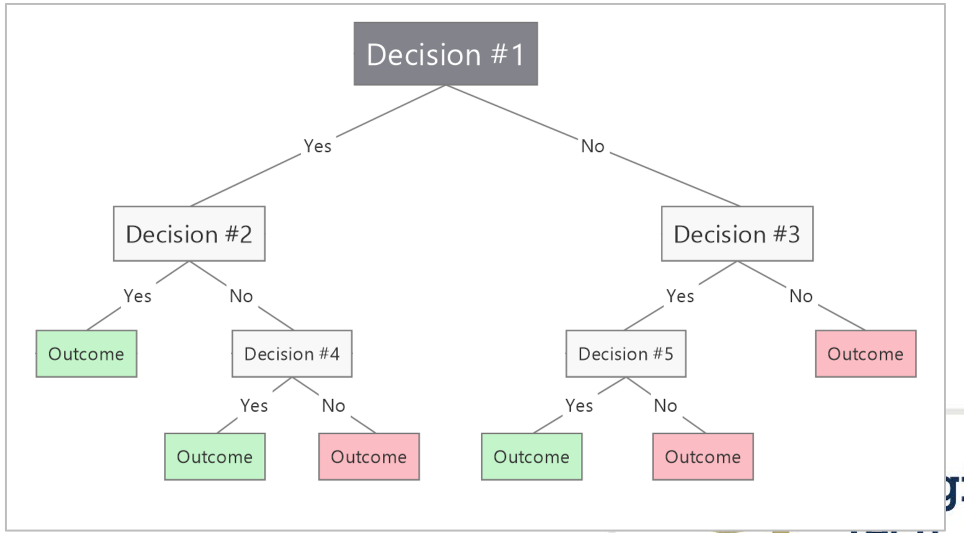
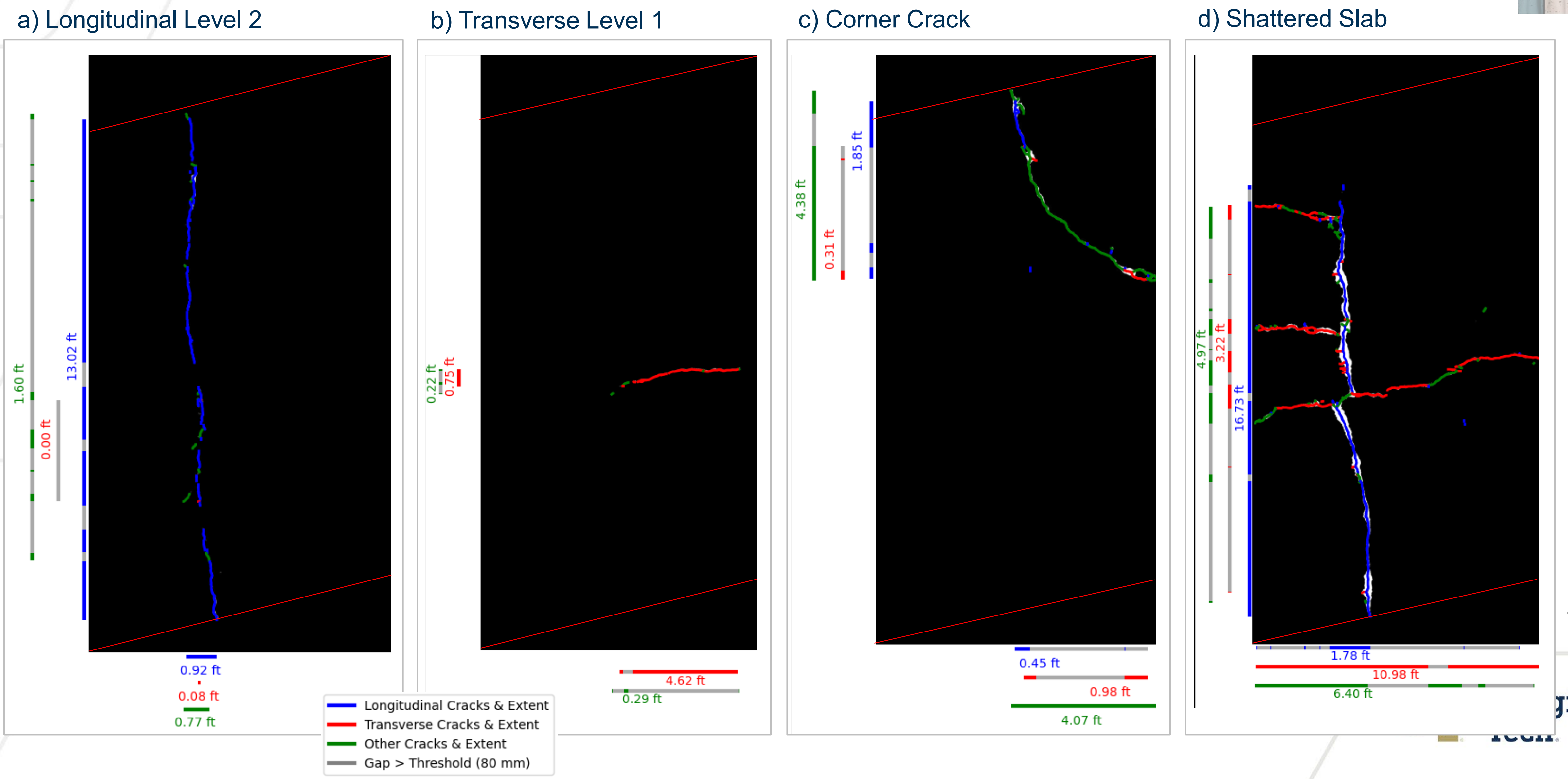


Figure from https://blog.mindmanager.com/decision-tree-diagrams/

Additional Explanation of the Proposed Methodology

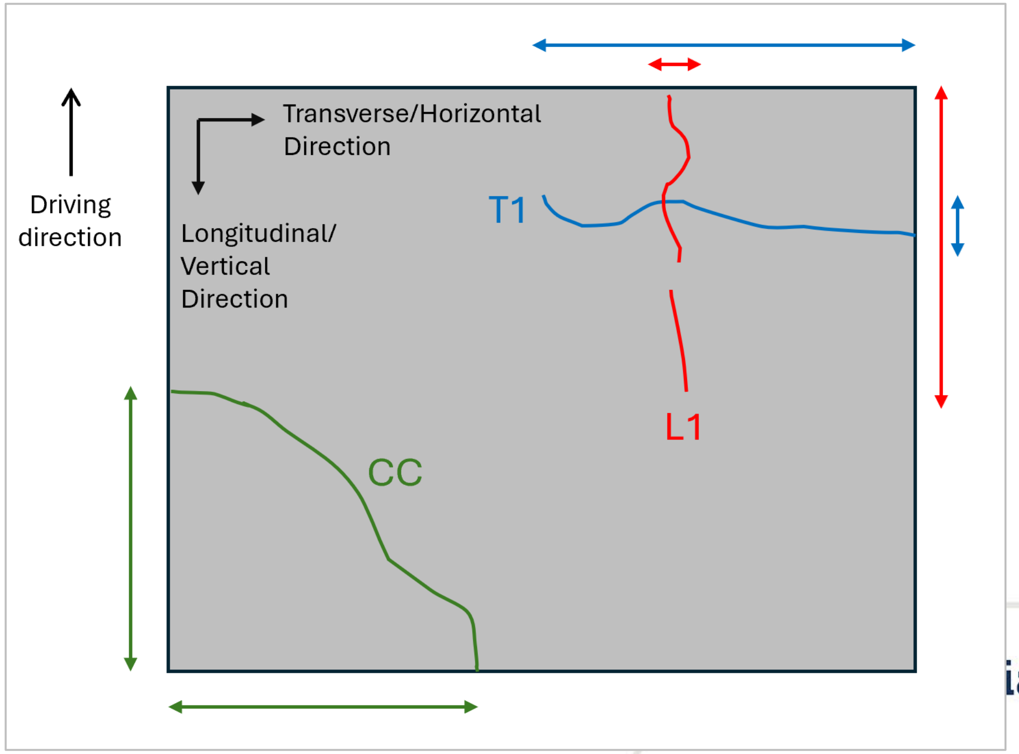


Input Data for the Decision Tree Model

- Target Variable: Slab Type (SS, CC, L1, L2, T1, T2)

- Features:

1) Longitudinal Crack Extent (horizontal axis) (ft)
2) Longitudinal Crack Extent (vertical axis) (ft)
3) Transverse Crack Extent (horizontal axis) (ft)
4) Transverse Crack Extent (vertical axis) (ft)
5) Other Crack Extent (horizontal axis) (ft)
6) Other Crack Extent (vertical axis) (ft)
7) Total Longitudinal Crack Gap (ft)
8) Total Transverse Crack Gap (ft)
9) Total Other Crack Gap (ft)
10) Distance from Longitudinal Cracks to the Nearest Horizontal Joint (ft)
11) Distance from Longitudinal Cracks to the Nearest Vertical Joint (ft)
12) Distance from Transverse Cracks to the Nearest Horizontal Joint (ft)
13) Distance from Transverse Cracks to the Nearest Vertical Joint (ft)
14) Distance from Other Cracks to the Nearest Horizontal Joint (ft)
15) Distance from Other Cracks to the Nearest Vertical Joint (ft)
16) Ratio of Vertical to Horizontal Extent for Other Cracks
17) Ratio of Longitudinal Crack Extent to Slab Length
18) Longitudinal and Transverse Cracks Intersect
19) Crack Extent (vertical axis) (ft)
20) Crack Extent (horizontal axis) (ft)
21) Total Gap (vertical axis) (ft)
22) Total Gap (horizontal axis) (ft)
23) Ratio of Vertical Extent to Slab Length
24) Ratio of Vertical to Horizontal Extent
25) Distance from Cracks to the Top Horizontal Joint (ft)
26) Distance from Cracks to the Bottom Horizontal Joint (ft)
27) Distance from Cracks to the Left Transverse Joint (ft)
28) Distance from Cracks to the Right Transverse Joint (ft)
29) Distance from Cracks to the Nearest Horizontal Joint (ft)
30) Distance from Cracks to the Nearest Vertical Joint (ft)



Decision Tree with Stratified Sampling and GridSearchCV

- Steps for Decision Tree Modeling:
  1) Data Split: Split the dataset into Training (80%) and Testing (20%) sets using Stratified Sampling to ensure class distribution is maintained in both sets.
  2) GridSearchCV & Hyperparameter Tuning:
     - Run GridSearchCV on the Training Set with 4-fold stratified cross-validation.
     - Fine-tune key parameters:
       - max_depth
       - min_samples_split
       - min_samples_leaf
       - criterion (Gini/Entropy)
     - Identify the best model based on training scores (Weighted F1-Score).
  3) Test Set Evaluation:
     - Evaluate the best model's performance on the Testing Set.
     - Metrics include:
       - Accuracy / Weighted F1-Score
       - Classification Report
       - Confusion Matrix
  4) Visualization & Export:
     - Visualize the decision tree structure.
     - Export rules and decision paths for interpretability.

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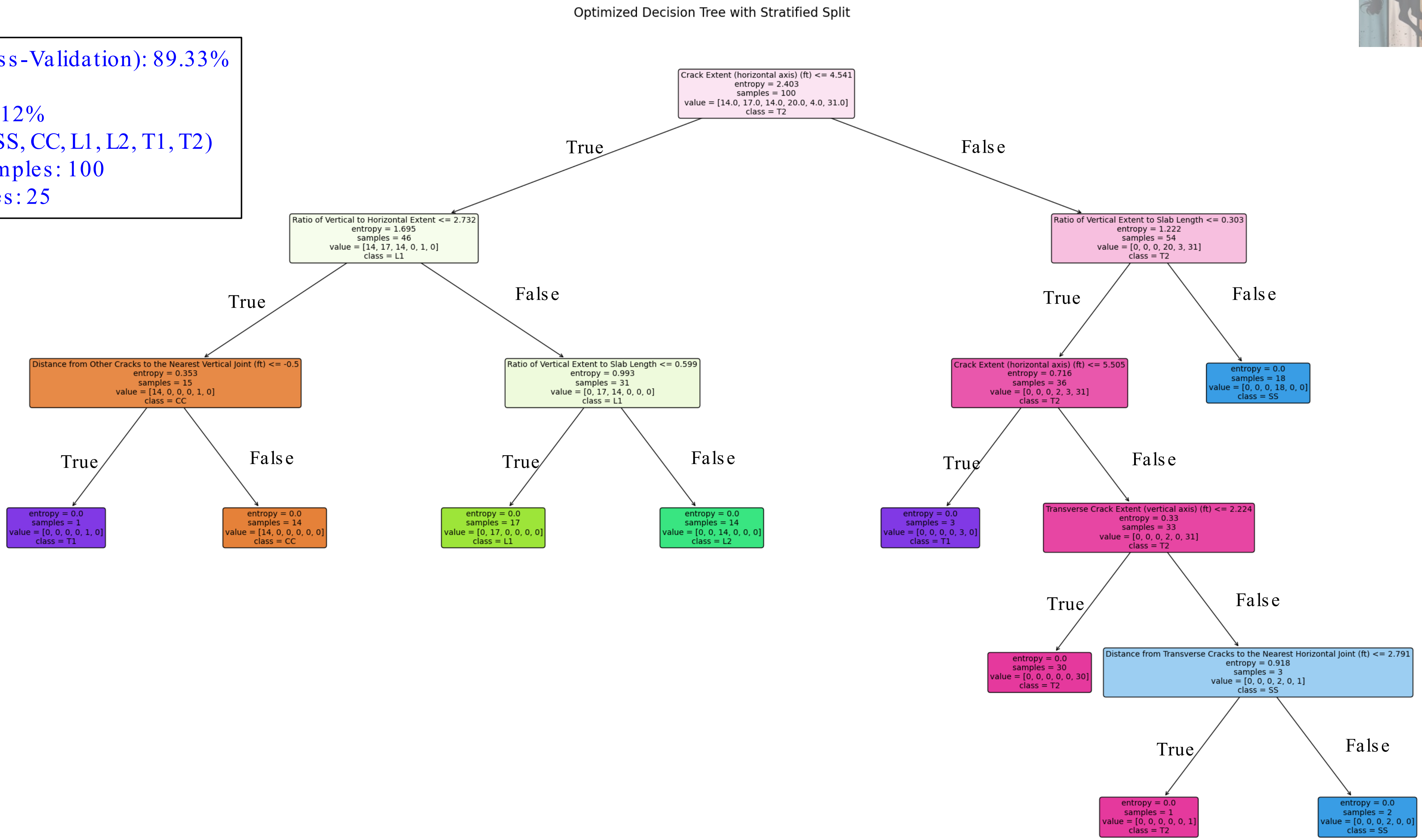
Decision Tree Established with 30 Features as Input

- Training Accuracy (Cross-Validation): 89.33%
- Test Accuracy: 88.00%
- Weighted F1-Score: 86.12%
- Number of Classes: 6 (SS, CC, L1, L2, T1, T2)
- Number of Training Samples: 100
- Number of Test Samples: 25



Decision Tree Established with 30 Features as Input (cont’d)


```
|--- Crack Extent (horizontal axis) (ft) <= 4.54
|   |--- Ratio of Vertical to Horizontal Extent <= 2.73
|   |   |--- Distance from Other Cracks to the Nearest Vertical Joint (ft) <= -0.50
|   |   |   |--- class: T1
|   |   |--- Distance from Other Cracks to the Nearest Vertical Joint (ft) >  -0.50
|   |   |   |--- class: CC
|   |--- Ratio of Vertical to Horizontal Extent >  2.73
|   |   |--- Ratio of Vertical Extent to Slab Length <= 0.60
|   |   |   |--- class: L1
|   |   |--- Ratio of Vertical Extent to Slab Length >  0.60
|   |   |   |--- class: L2
|--- Crack Extent (horizontal axis) (ft) >  4.54
|   |--- Ratio of Vertical Extent to Slab Length <= 0.30
|   |   |--- Crack Extent (horizontal axis) (ft) <= 5.51
|   |   |   |--- class: T1
|   |   |--- Crack Extent (horizontal axis) (ft) >  5.51
|   |   |   |--- Transverse Crack Extent (vertical axis) (ft) <= 2.22
|   |   |   |   |--- class: T2
|   |   |   |--- Transverse Crack Extent (vertical axis) (ft) >  2.22
|   |   |   |   |--- Distance from Transverse Cracks to the Nearest Horizontal Joint (ft) <= 2.79
|   |   |   |   |   |--- class: T2
|   |   |   |   |--- Distance from Transverse Cracks to the Nearest Horizontal Joint (ft) >  2.79
|   |   |   |   |   |--- class: SS
|   |--- Ratio of Vertical Extent to Slab Length >  0.30
|   |   |--- class: SS
```

Features:
1. Crack Extent (horizontal axis) (ft)
2. Ratio of Vertical to Horizontal Extent
3. Ratio of Vertical Extent to Slab Length
4. Distance from Other Cracks to the Nearest Vertical Joint (ft)
5. Transverse Crack Extent (vertical axis) (ft)
6. Distance from Transverse Cracks to the Nearest Horizontal Joint (ft)

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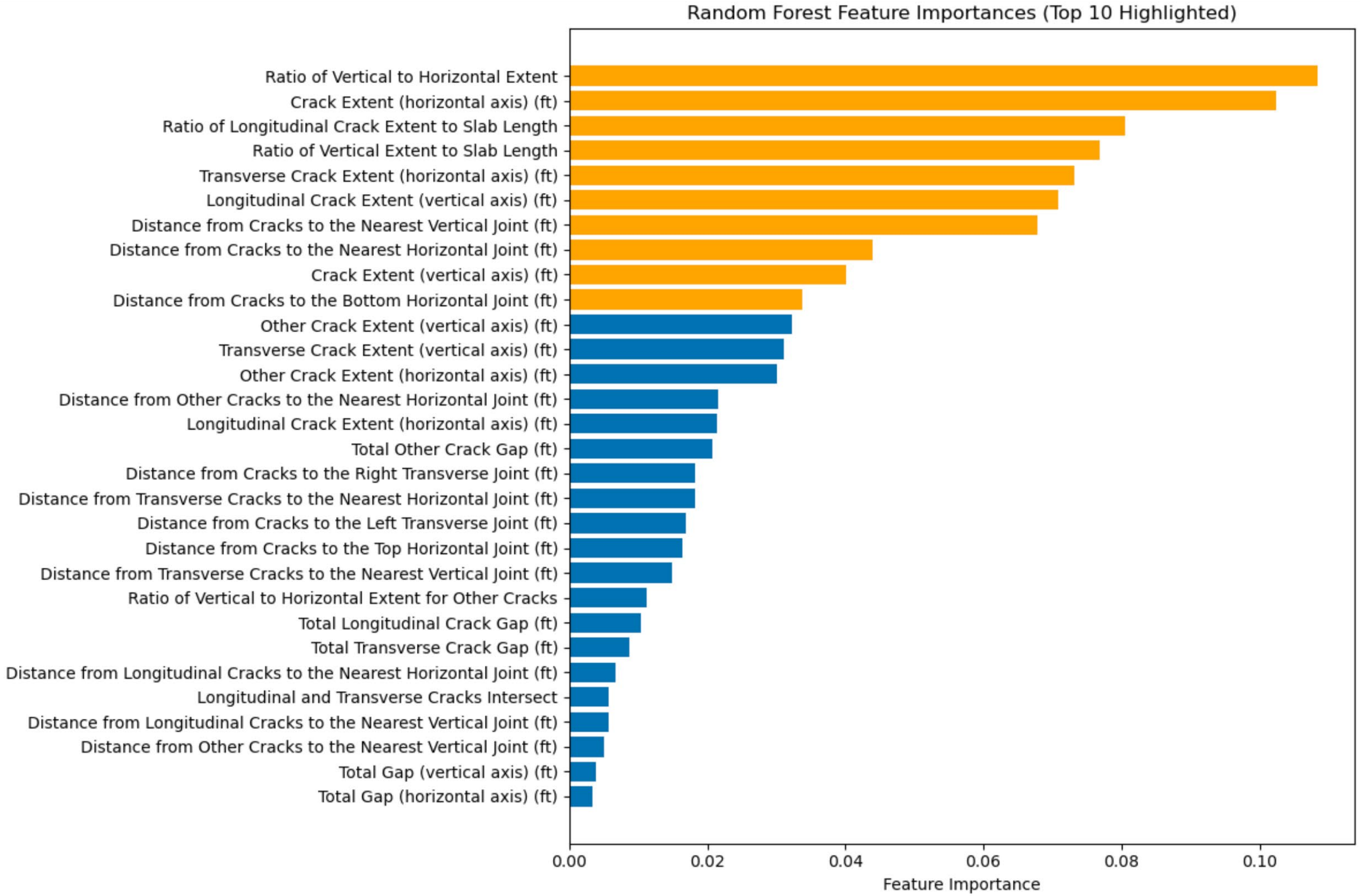
Decision Tree Performance with 30 Features and Analysis of Top 10 Important Features

```
Classification Report (Random Forest):
              precision    recall  f1-score   support

          CC       0.67      0.67      0.67         3
          L1       0.83      1.00      0.91         5
          L2       1.00      1.00      1.00         3
          SS       1.00      1.00      1.00         5
          T1       0.00      0.00      0.00         1
          T2       1.00      1.00      1.00         8

    accuracy                           0.92        25
   macro avg       0.75      0.78      0.76        25
weighted avg       0.89      0.92      0.90        25

Confusion Matrix (Random Forest):
[[2 1 0 0 0 0]
 [0 5 0 0 0 0]
 [0 0 3 0 0 0]
 [0 0 0 5 0 0]
 [1 0 0 0 0 0]
 [0 0 0 0 0 8]]
```

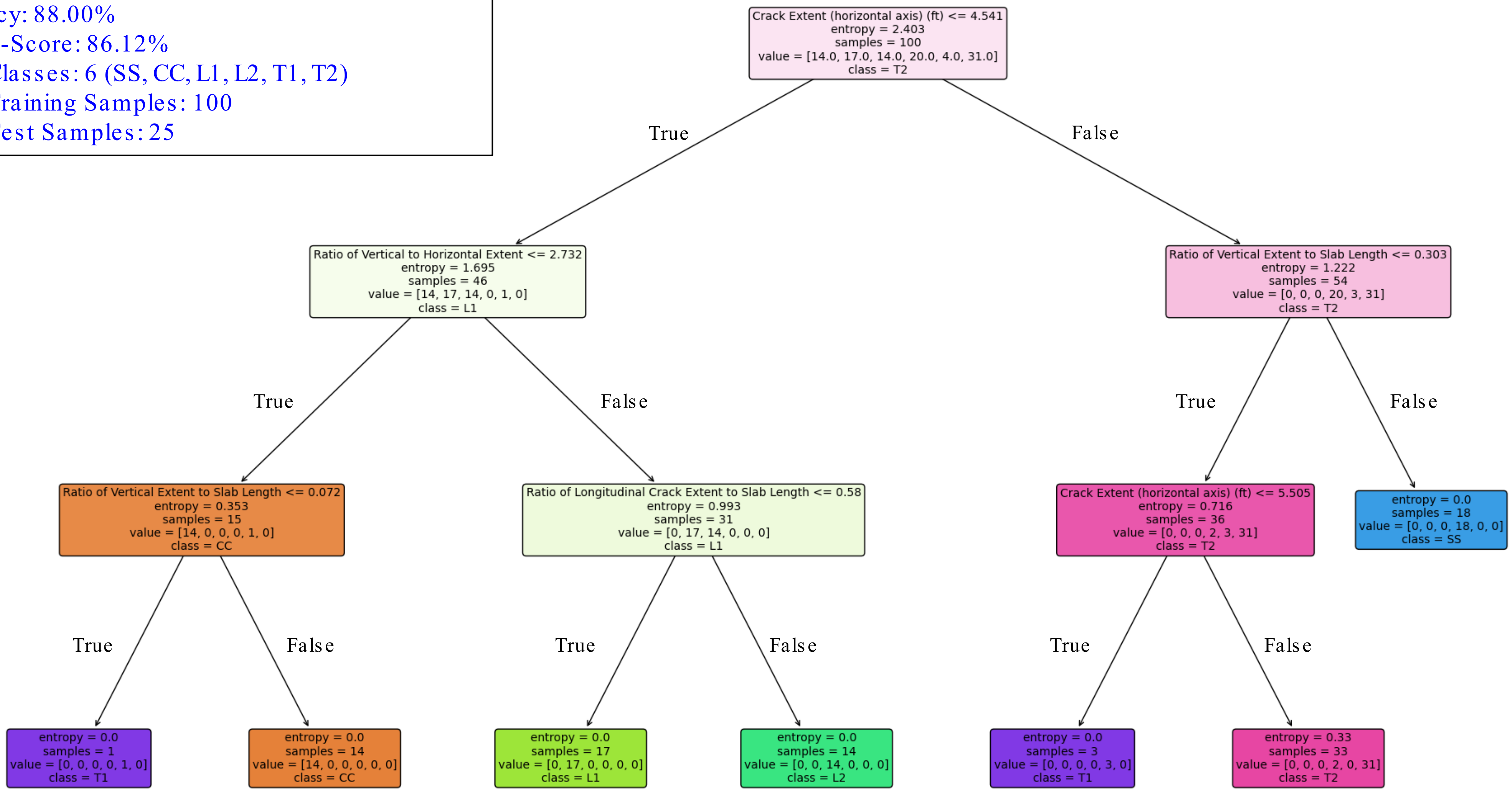


Tech

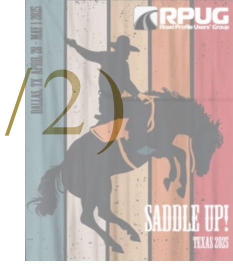
Decision Tree Performance with Top 10 Features (1/2)

- Training Accuracy (Cross-Validation): 89.43%
- Test Accuracy: 88.00%
- Weighted F1-Score: 86.12%
- Number of Classes: 6 (SS, CC, L1, L2, T1, T2)
- Number of Training Samples: 100
- Number of Test Samples: 25

Optimized Decision Tree Trained on Top 10 Features with Stratified Split



Decision Tree Performance with Top 10 Features (2/2)




```
|--- Crack Extent (horizontal axis) (ft) <= 4.54
|   |--- Ratio of Vertical to Horizontal Extent <= 2.73
|   |   |--- Ratio of Vertical Extent to Slab Length <= 0.07
|   |   |   |--- class: T1
|   |   |--- Ratio of Vertical Extent to Slab Length >  0.07
|   |   |   |--- class: CC
|   |--- Ratio of Vertical to Horizontal Extent >  2.73
|   |   |--- Ratio of Longitudinal Crack Extent to Slab Length <= 0.58
|   |   |   |--- class: L1
|   |   |--- Ratio of Longitudinal Crack Extent to Slab Length >  0.58
|   |   |   |--- class: L2
|--- Crack Extent (horizontal axis) (ft) >  4.54
|   |--- Ratio of Vertical Extent to Slab Length <= 0.30
|   |   |--- Crack Extent (horizontal axis) (ft) <= 5.51
|   |   |   |--- class: T1
|   |   |--- Crack Extent (horizontal axis) (ft) >  5.51
|   |   |   |--- class: T2
|   |--- Ratio of Vertical Extent to Slab Length >  0.30
|   |   |--- class: SS
```

Features:

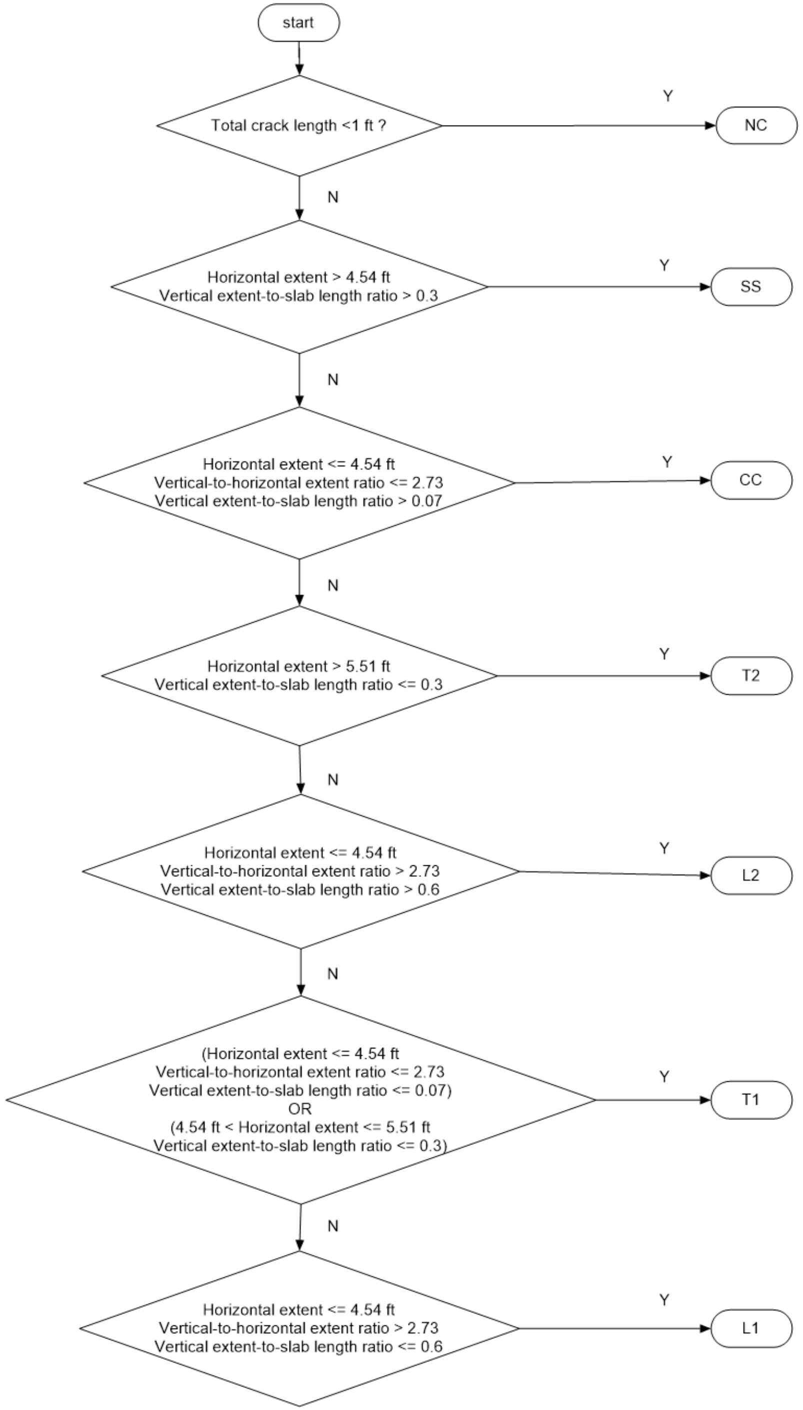
1. Crack Extent (horizontal axis) (ft)
2. Ratio of Vertical to Horizontal Extent
3. Ratio of Vertical Extent to Slab Length
4. Ratio of Longitudinal Crack Extent to Slab Length

JCPC Classification Flow Chart Established Using the Knowledge Extracted from the Decision Tree

- Key features and thresholds are extracted from the decision tree that can be used to establish an easy and implementable flow chart for slab state classification.

Three key features:

1. Crack Extent (horizontal axis) (ft)
2. Ratio of Vertical to Horizontal Extent
3. Ratio of Vertical Extent to Slab Length



Decision Tree: Class Performance Insights

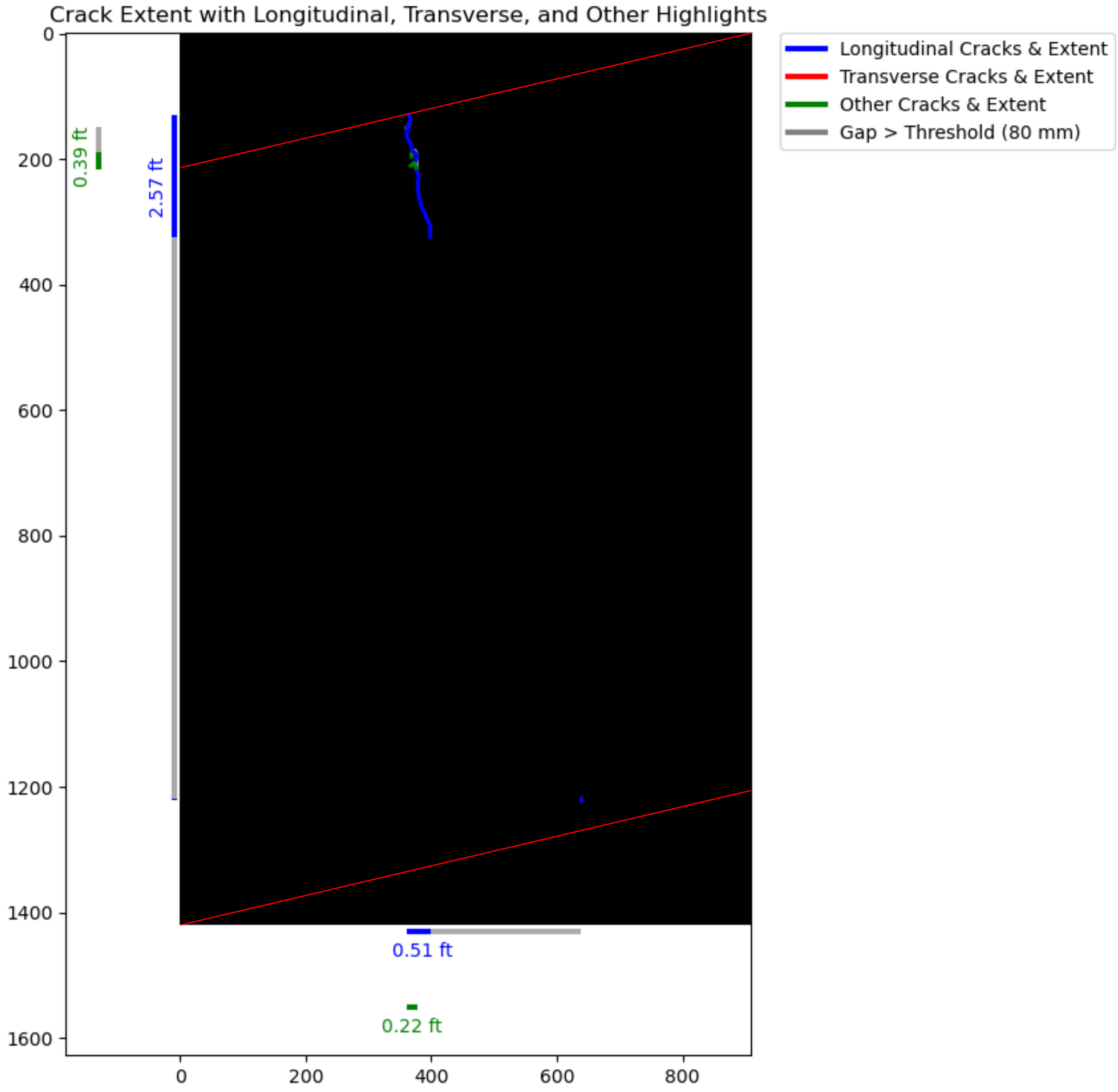
1) Strong Classes:
   - L2 (Longitudinal Slabs) and SS (Shattered Slabs):
     - Perfect precision, recall, and F1-score.
     - The model confidently predicts these classes without misclassifications.
   - T2 (Transverse Slabs):
     - High precision (89%) and perfect recall (100%).
     - Misclassifications are minimal.
2) Intermediate Classes:
   - L1 (Longitudinal Slabs):
     - Good precision, recall, and F1-score (80%), but some misclassifications into CC.
3) Weak Classes:
   - T1 (Transverse Slabs):
     - Precision, recall, and F1-score are all 0.
     - Indicates no correct predictions for this class.
     - Reason: Only one instance in the test set. This suggests insufficient data for the model to learn this class effectively.
   - CC (Corner Cracked Slabs):
     - Moderate precision, recall, and F1-score (67%).
     - Misclassifications into L1 and T1, as shown in the confusion matrix.

```
Classification Report:
              precision    recall  f1-score   support

          CC       0.67      0.67      0.67         3
          L1       0.80      0.80      0.80         5
          L2       1.00      1.00      1.00         3
          SS       1.00      1.00      1.00         5
          T1       0.00      0.00      0.00         1
          T2       0.89      1.00      0.94         8

    accuracy                           0.88        25
   macro avg       0.73      0.74      0.73        25
weighted avg       0.84      0.88      0.86        25
```

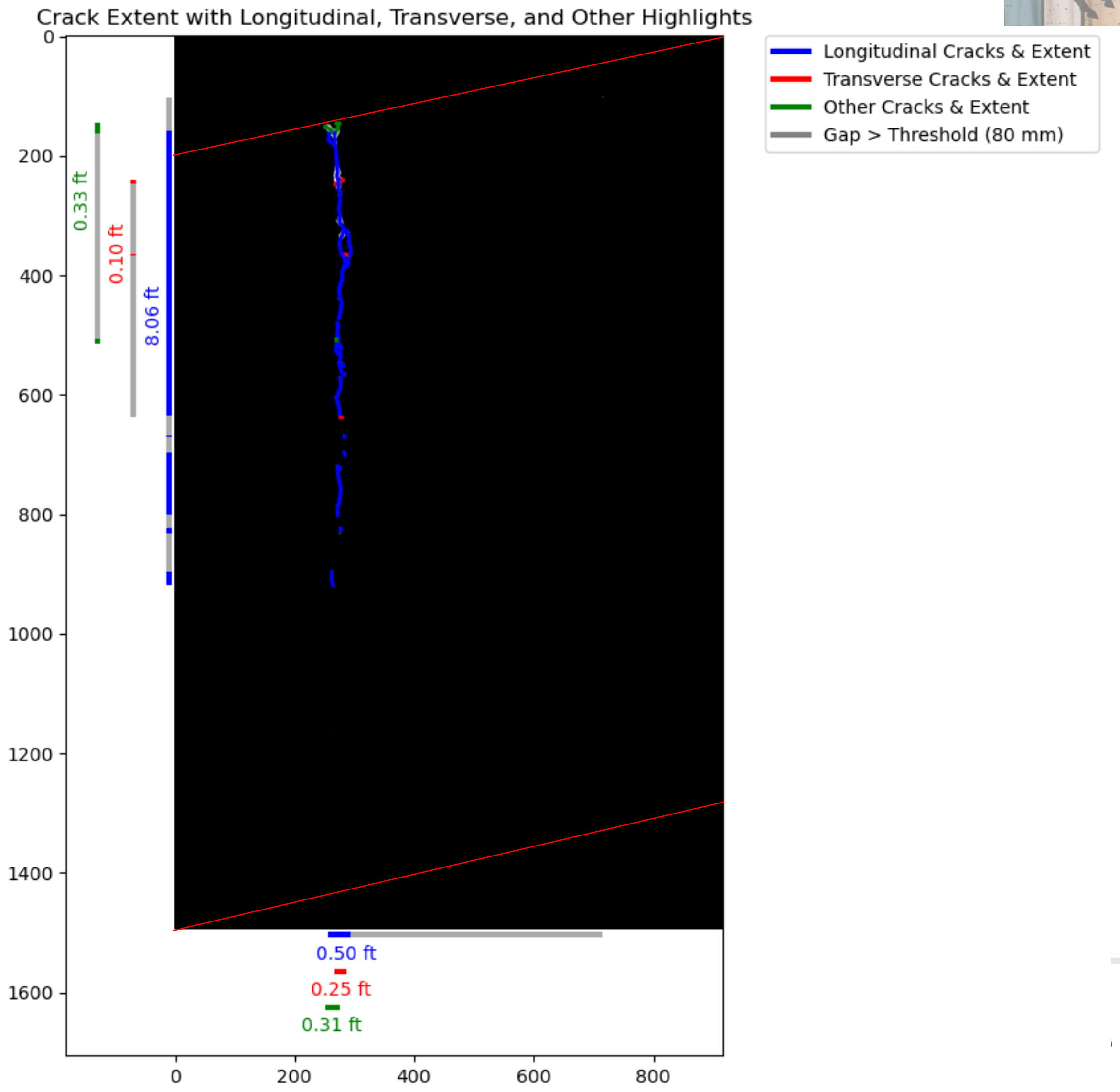
Confusion Matrix:

True \ Pred	CC	L1	L2	SS	T1	T2
CC	2	1	0	0	0	0
L1	1	4	0	0	0	0
L2	0	0	3	0	0	0
SS	0	0	0	5	0	0
T1	0	0	0	0	0	1
T2	0	0	0	0	0	8

L1 Slabs

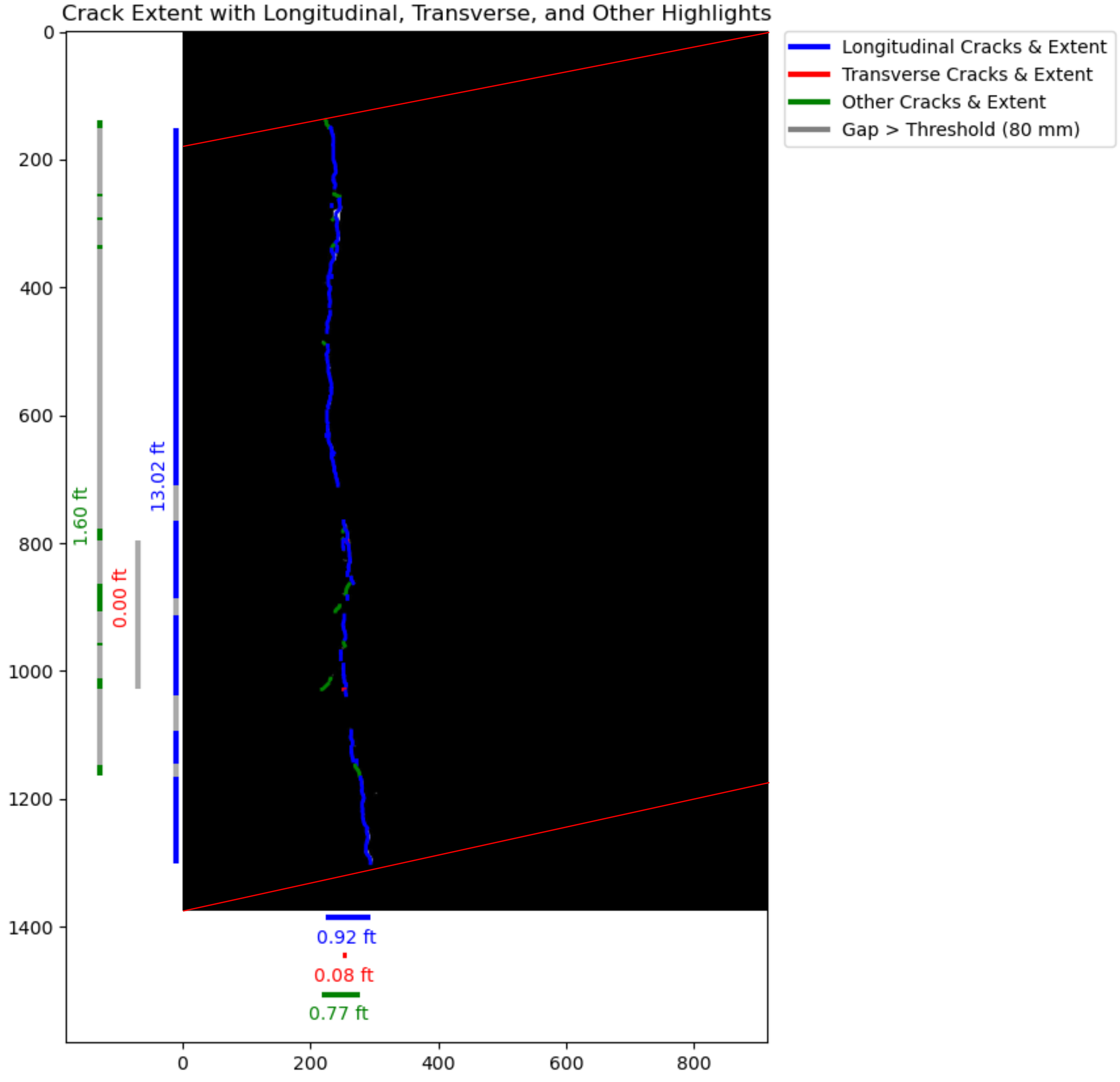


Crack Extent with Longitudinal, Transverse, and Other Highlights
Longitudinal Cracks & Extent
Transverse Cracks & Extent
Other Cracks & Extent
Gap > Threshold (80 mm)
0.39 ft
2.57 ft
0.51 ft
0.22 ft
0
200
400
600
800
1000
1200
1400
1600

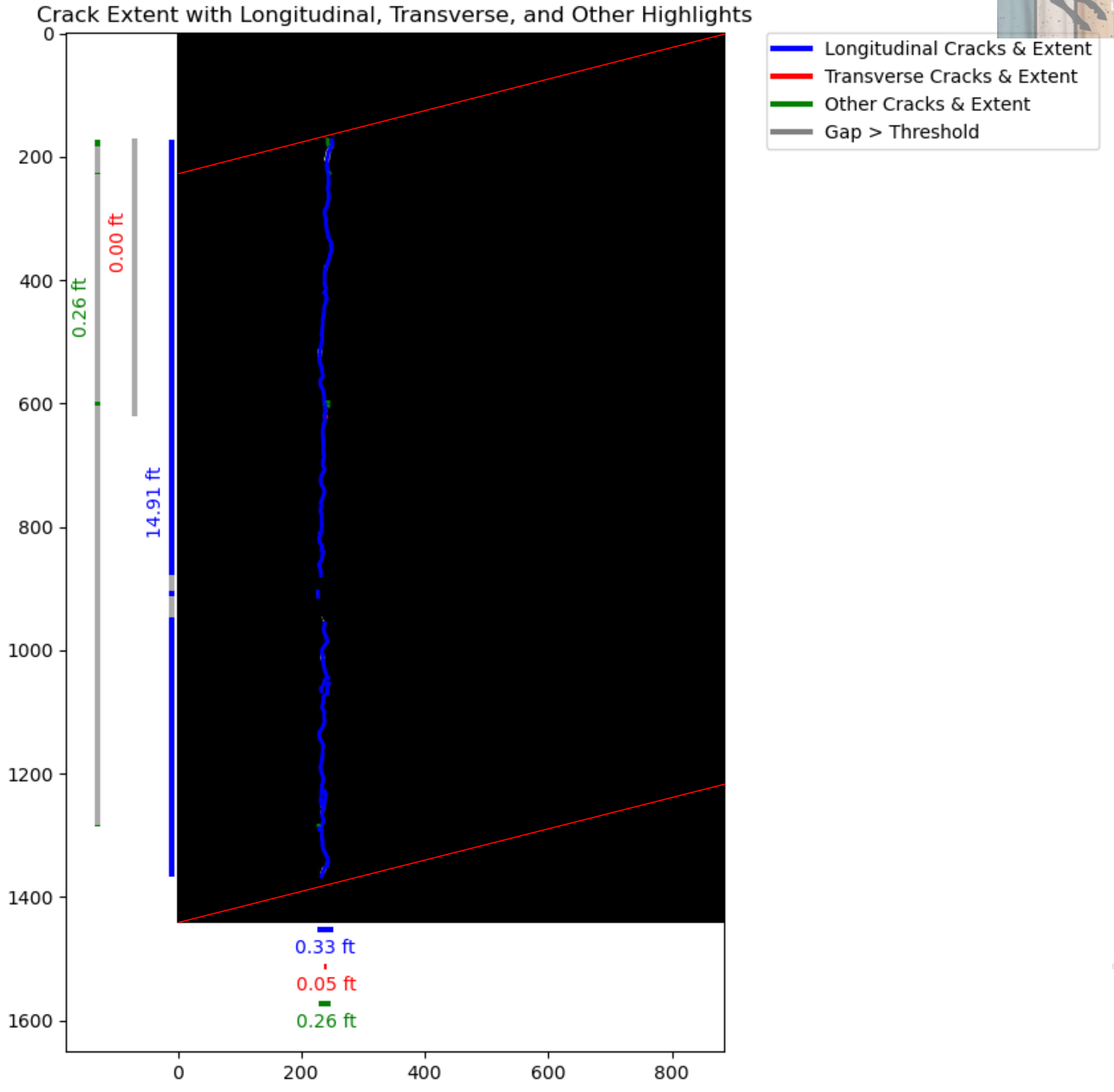


Crack Extent with Longitudinal, Transverse, and Other Highlights
Longitudinal Cracks & Extent
Transverse Cracks & Extent
Other Cracks & Extent
Gap > Threshold (80 mm)
0.33 ft
0.10 ft
8.06 ft
0.50 ft
0.25 ft
0.31 ft
0
200
400
600
800
1000
1200
1400
1600

L2 Slabs

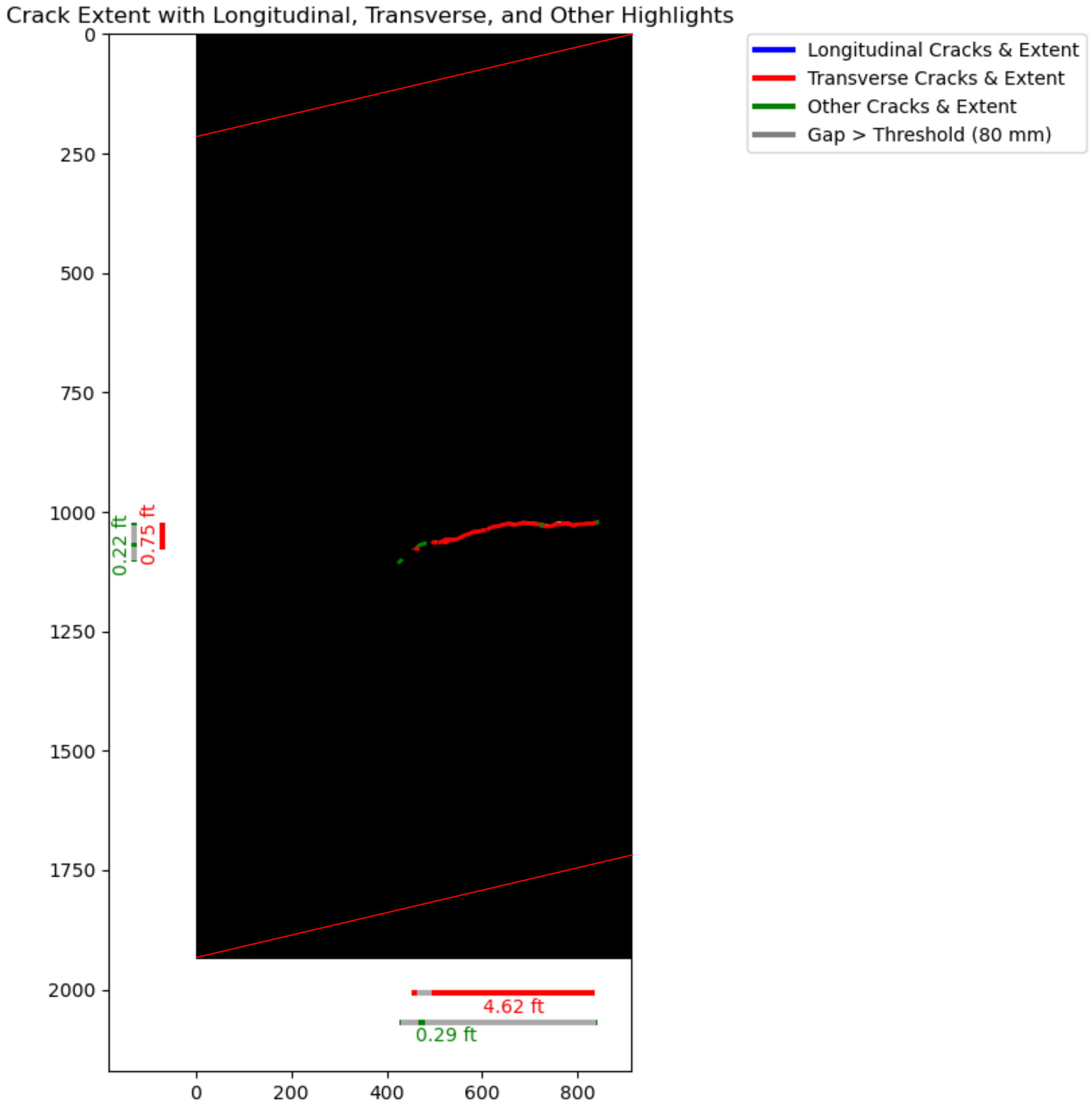


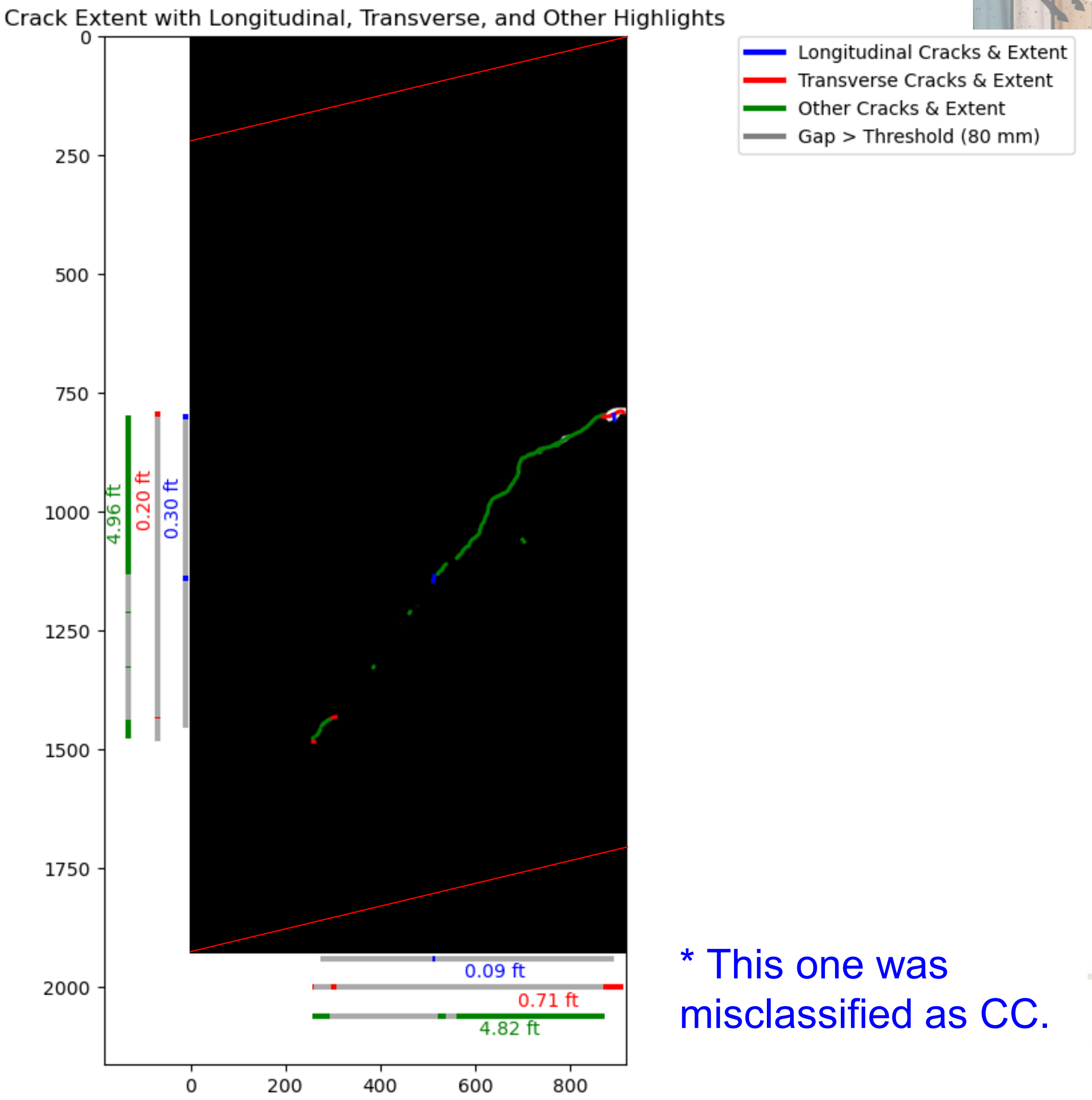
Crack Extent with Longitudinal, Transverse, and Other Highlights
Longitudinal Cracks & Extent
Transverse Cracks & Extent
Other Cracks & Extent
Gap > Threshold (80 mm)
1.60 ft
0.00 ft
13.02 ft
0.92 ft
0.08 ft
0.77 ft
0
200
400
600
800
1000
1200
1400



Crack Extent with Longitudinal, Transverse, and Other Highlights
Longitudinal Cracks & Extent
Transverse Cracks & Extent
Other Cracks & Extent
Gap > Threshold
0.26 ft
0.00 ft
14.91 ft
0.33 ft
0.05 ft
0.26 ft
0
200
400
600
800
1000
1200
1400
1600

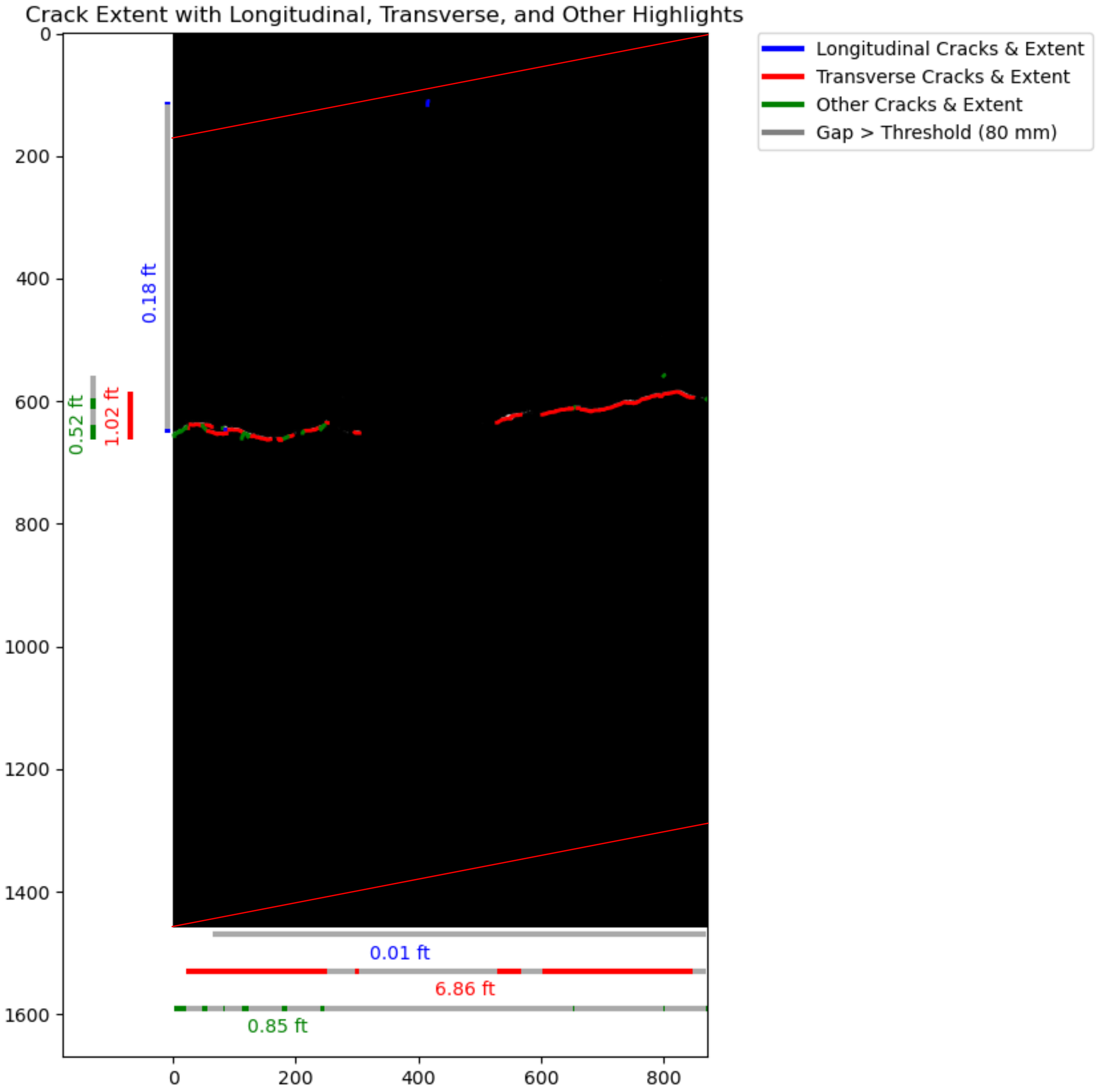
T1 Slabs



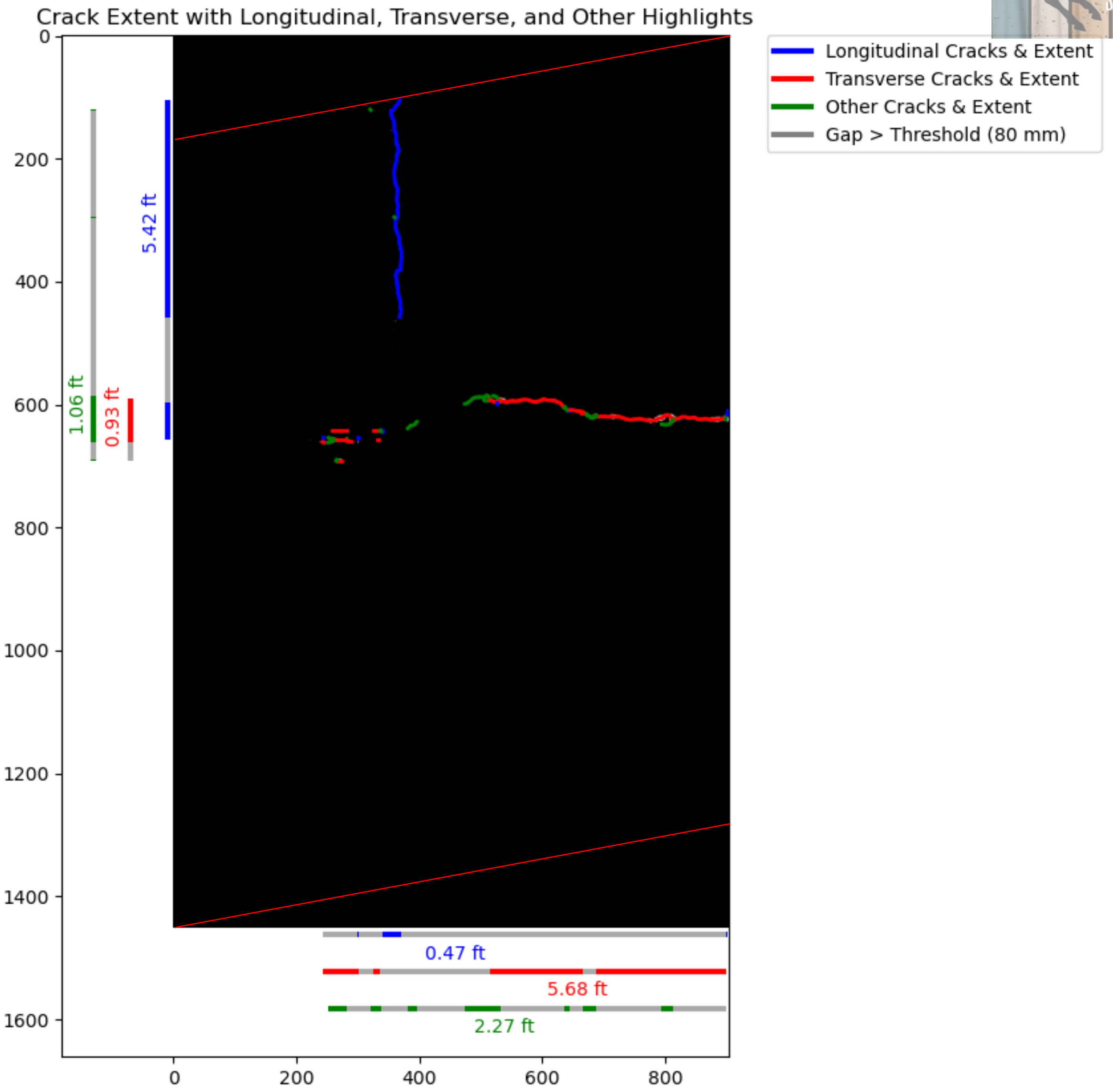


* This one was misclassified as CC.

T2 Slabs



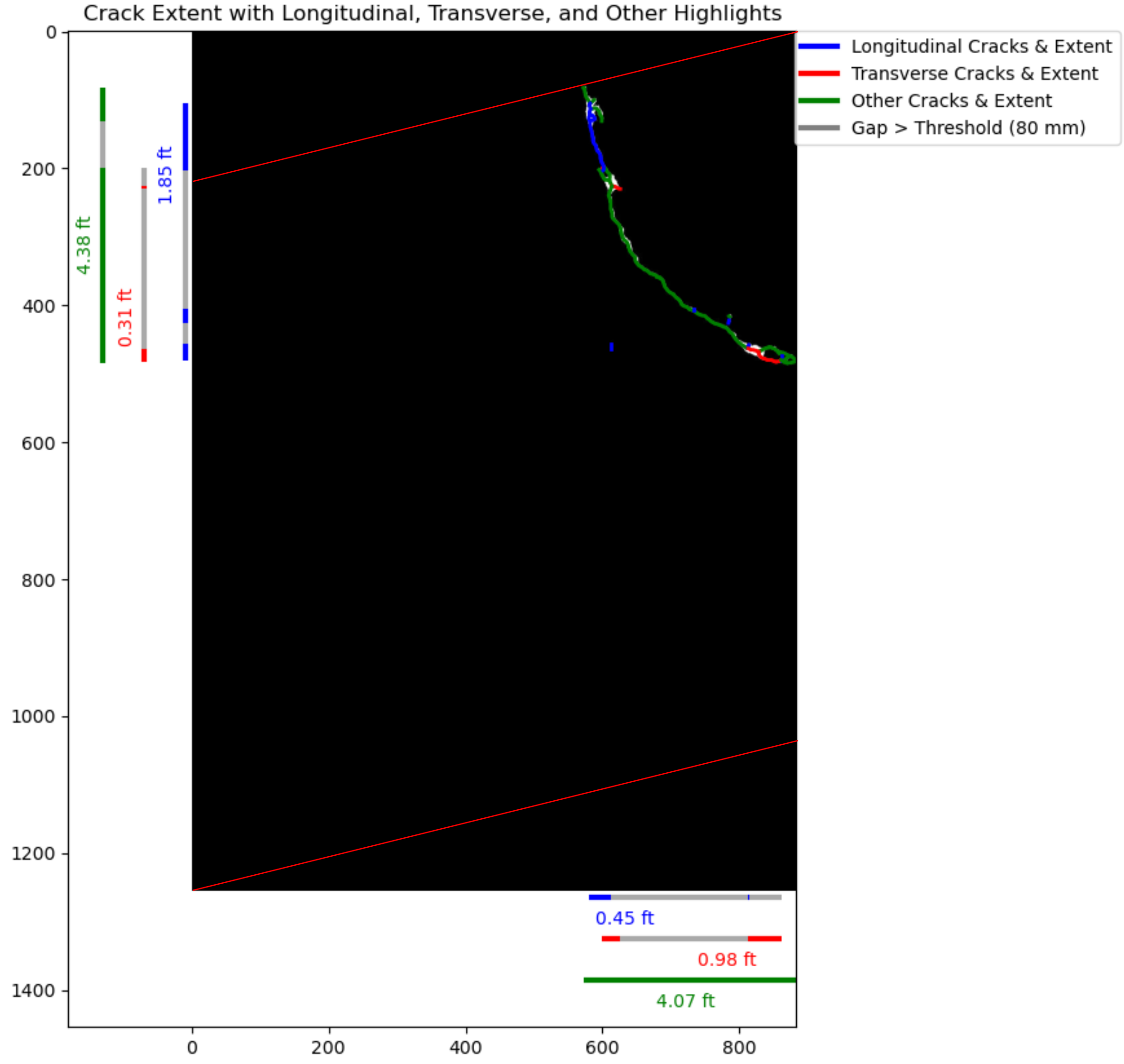
Crack Extent with Longitudinal, Transverse, and Other Highlights
Longitudinal Cracks & Extent
Transverse Cracks & Extent
Other Cracks & Extent
Gap > Threshold (80 mm)
0.18 ft
0.52 ft
1.02 ft
0.01 ft
6.86 ft
0.85 ft

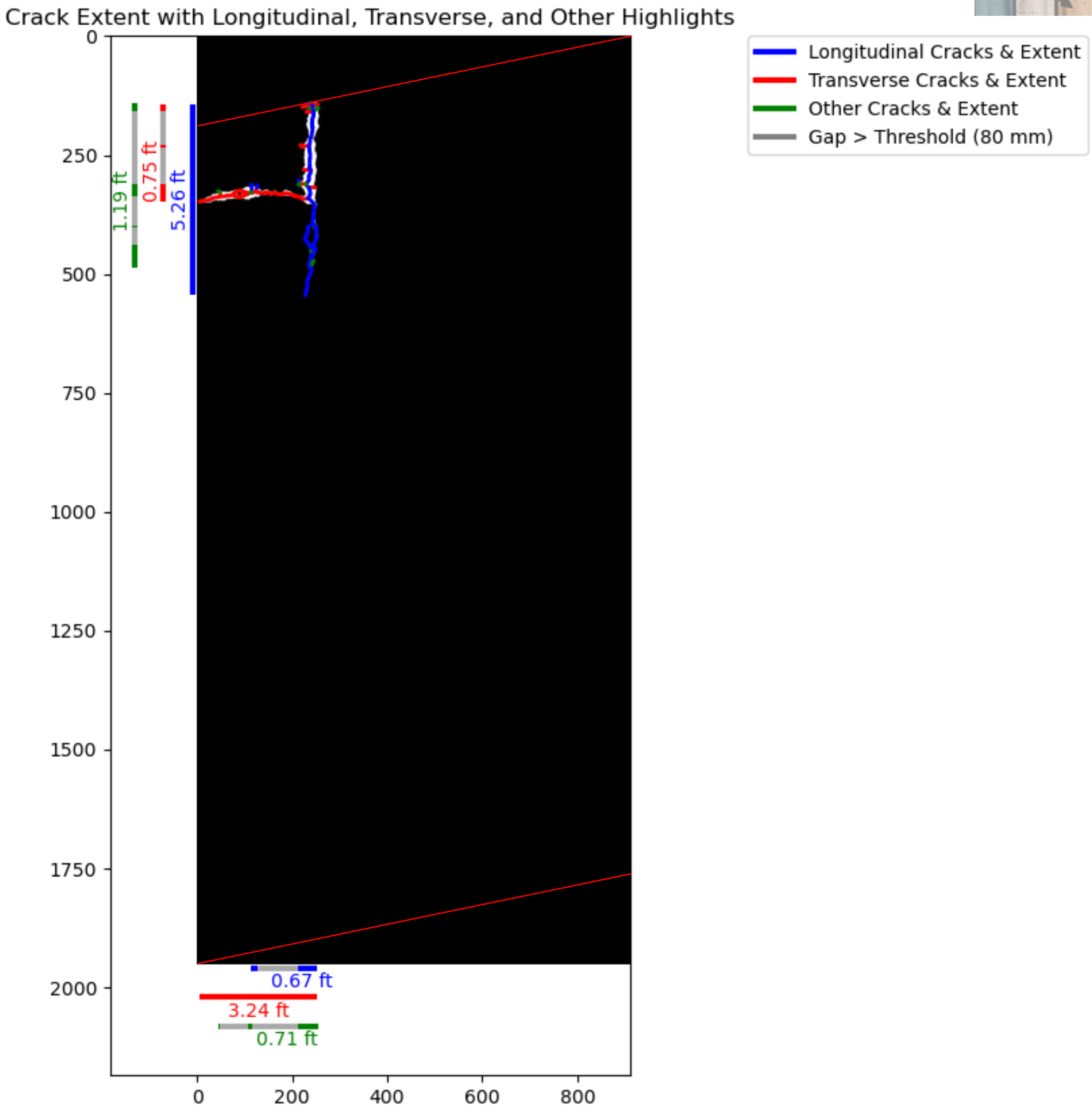


Crack Extent with Longitudinal, Transverse, and Other Highlights
Longitudinal Cracks & Extent
Transverse Cracks & Extent
Other Cracks & Extent
Gap > Threshold (80 mm)
5.42 ft
1.06 ft
0.93 ft
0.47 ft
5.68 ft
2.27 ft

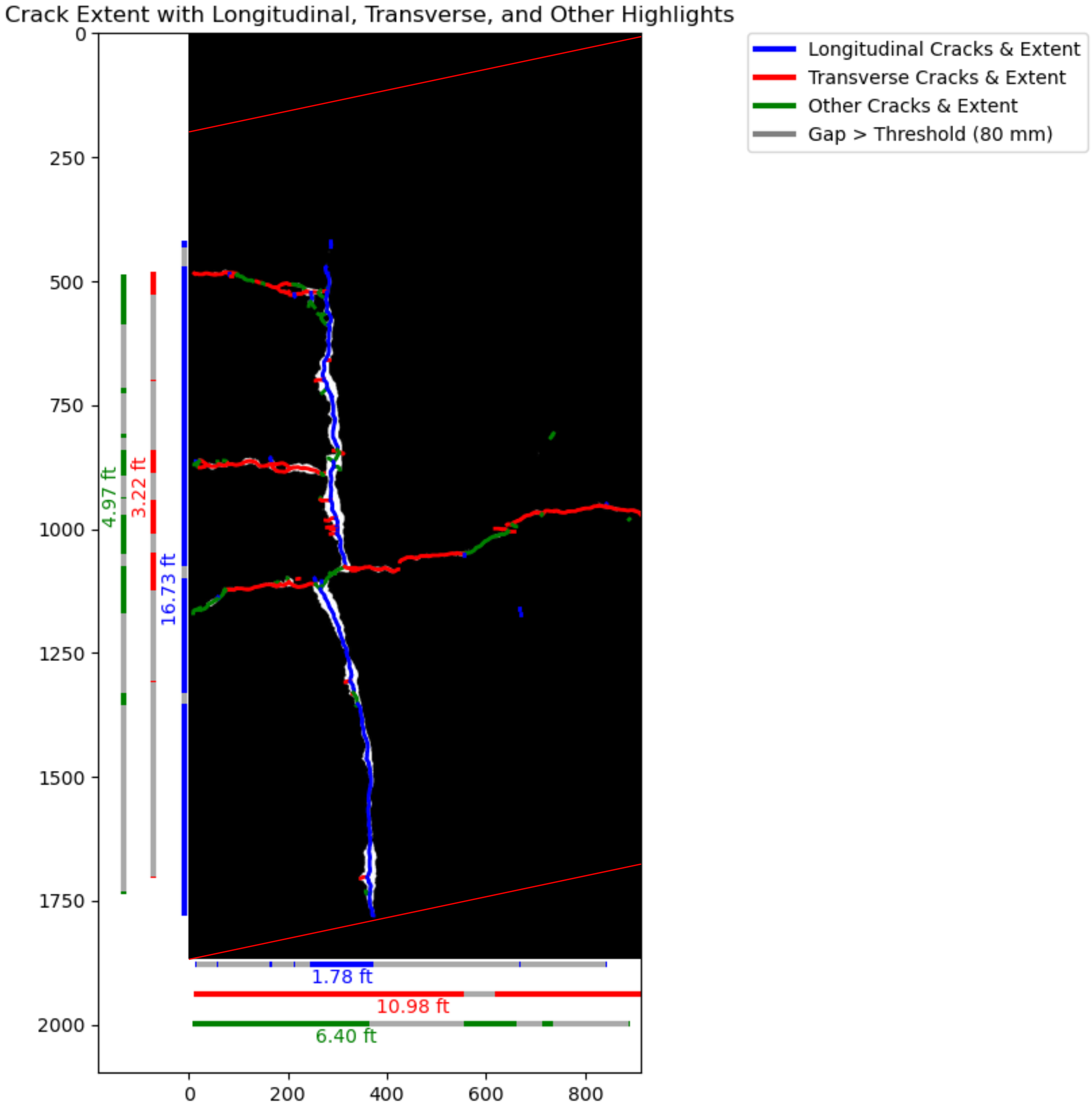
RPUG
SADDLE UP!

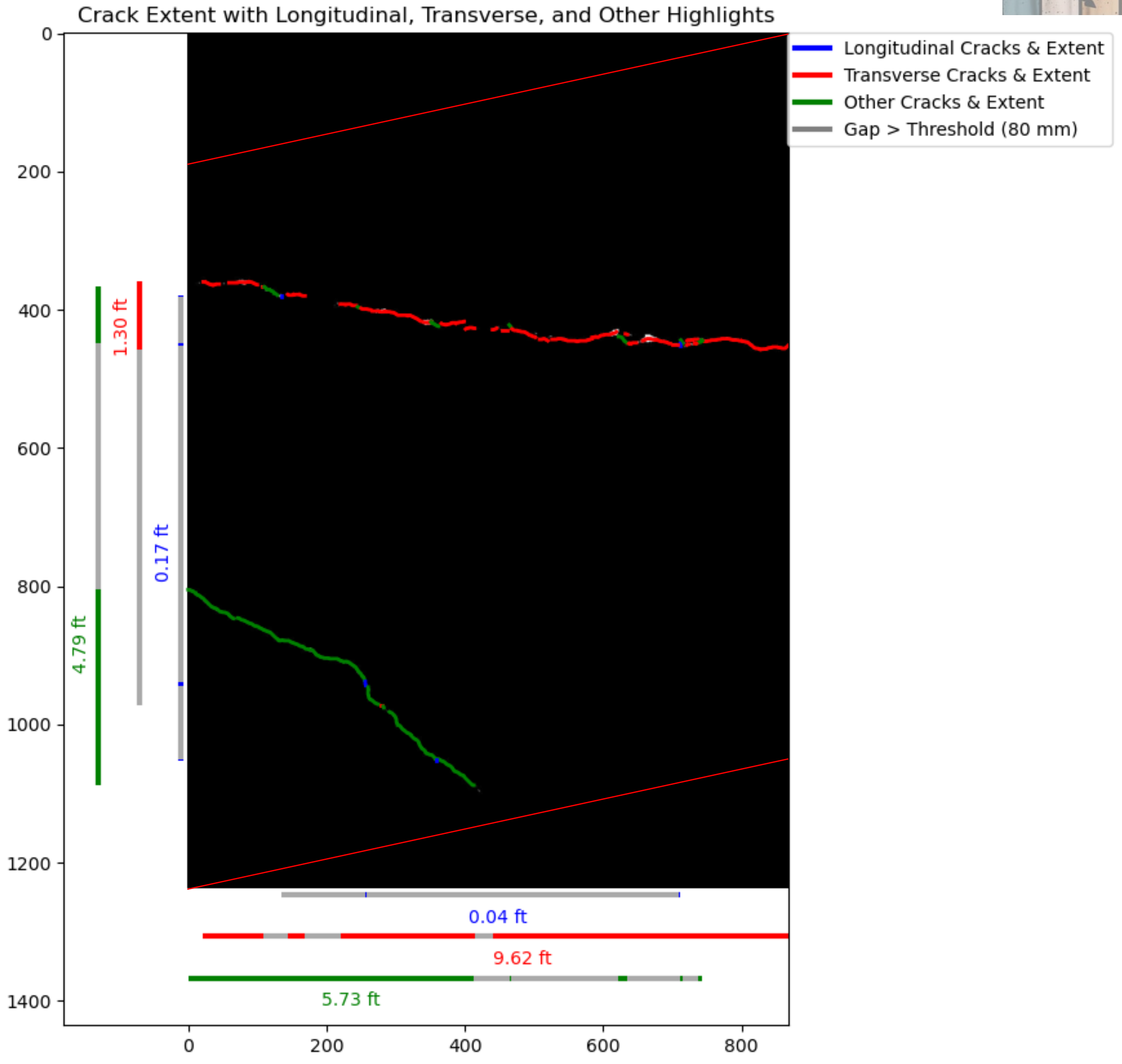
Corner Cracked Slabs





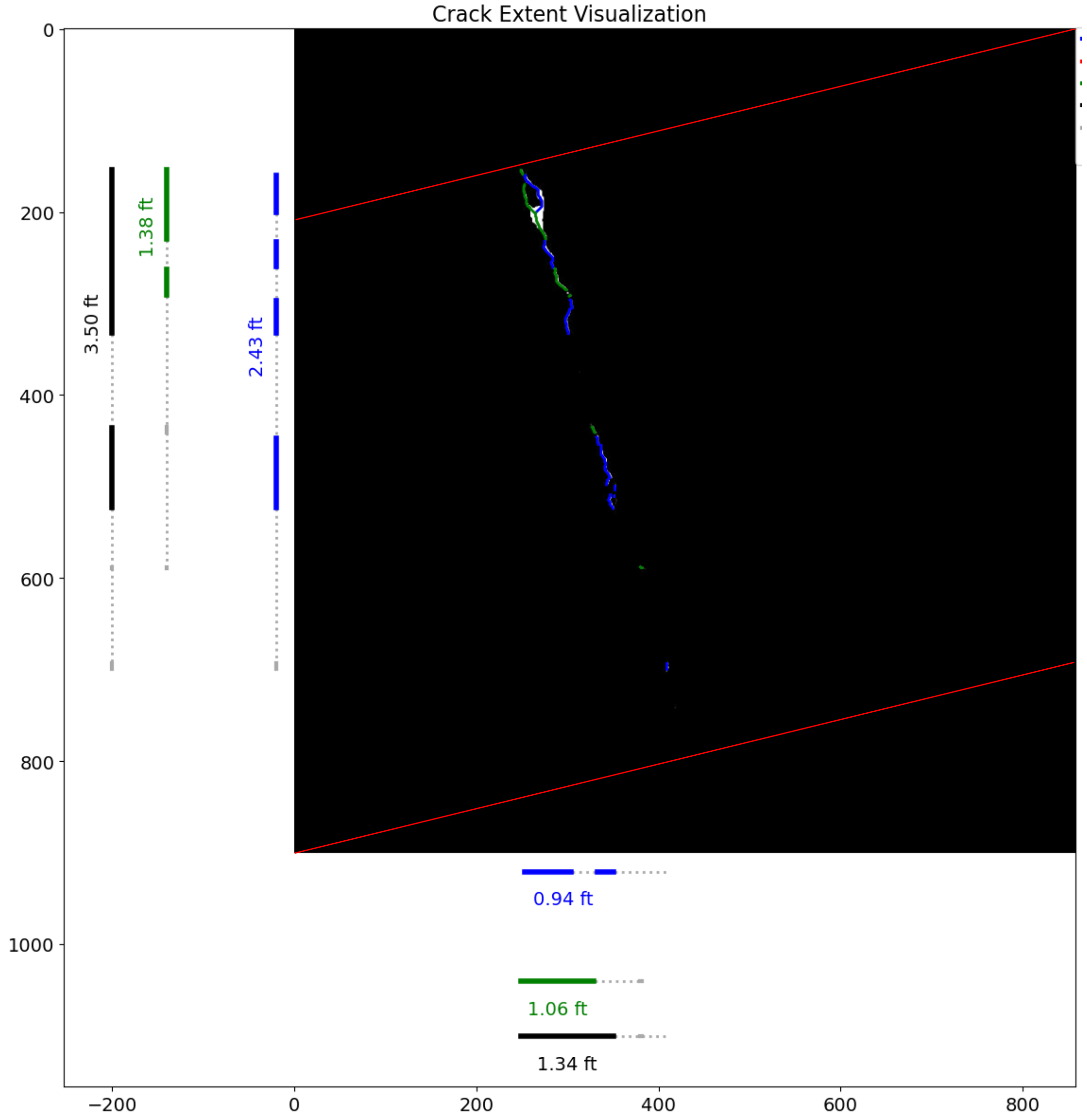
Shattered Slabs



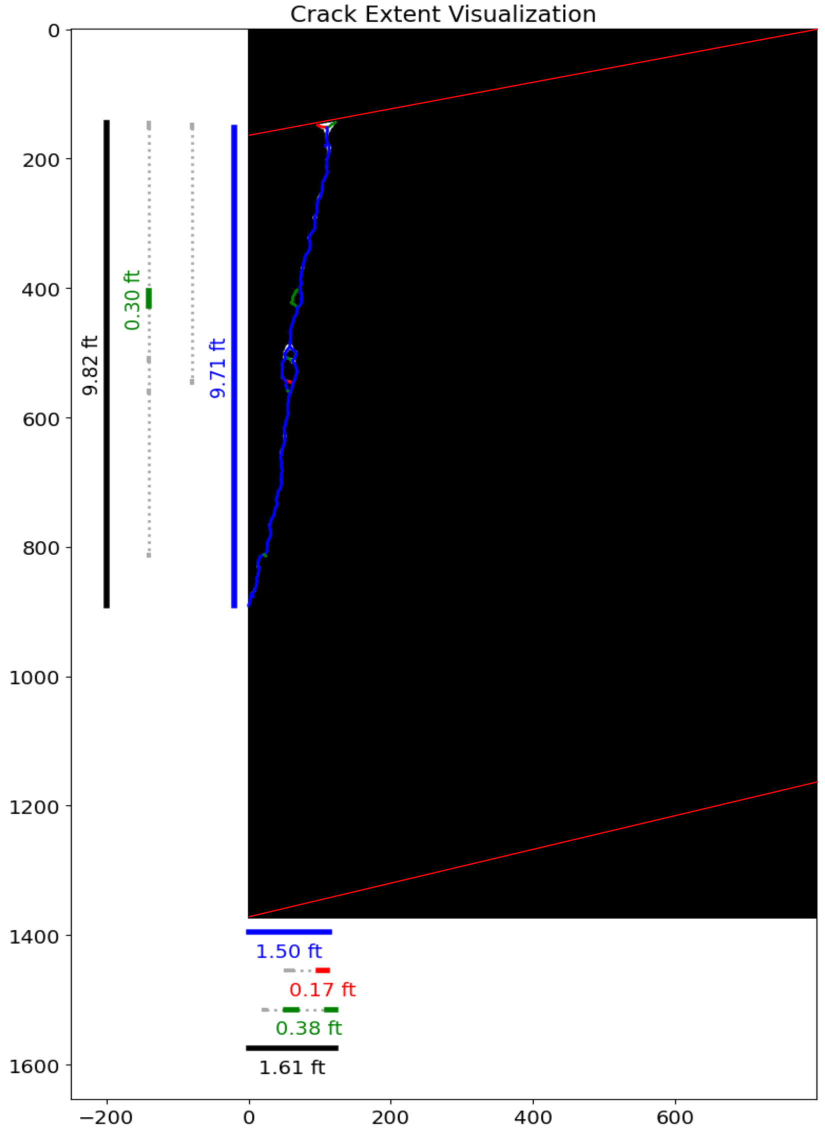


Misclassifications

L1 was misclassified as



CC was misclassified as



Conclusions

- This study proposes a novel methodology for automated and interpretable JPCP slab classification, aligned with a revised LTPP distress definition. An innovative Crack Vector Model (CVM) and a multi-dimensional cracking extent projection method are introduced to extract geometric features from crack maps, enabling the use of tree-based models for effective slab classification.
- The results show a weighted F1-score of 86.12%, comparable to that of a DL model, while tree-based models offer greater interpretability and ease of implementation.
- The improved interpretability and simplicity of this method facilitates its practical application in slab-based JPCP classification, supporting transportation agencies in achieving cost-effective, precision pavement maintenance.

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