

IMPLEMENTING AI/ML IN AUTOMATED PAVEMENT DISTRESS DETECTION AT THE STATE LEVEL -LESSONS LEARNED IN TEXAS

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OUTLINES



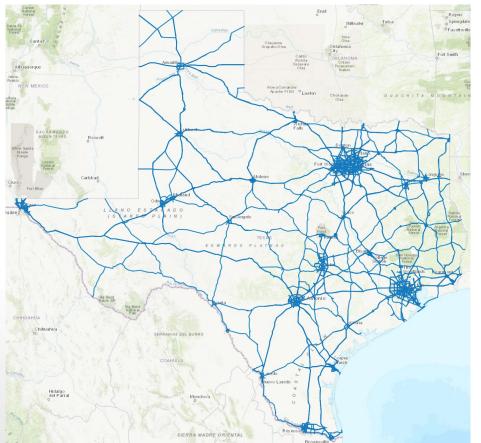
- INTRODUCTION
- PROJECT OVERVIEW
- LESSON 1: KNOW YOUR DATA
- LESSON 2: KNOW WHEN YOUR MODEL FAILS
- FUTURE DIRECTIONS



INTRODUCTION

- Distress detection model must operate reliably across an entire state-level highway network
- Errors at scale have real consequences
- Most existing research focuses on localized or Small-scale dataset
- The work addresses a critical gap







INTRODUCTION

- Characteristics varies depending on :
 - Pavement condition
 - Material type
 - Pavement age
 - Traffic pattern
 - Environmental exposure







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PROJECT OVERVIEW



TxDOT #7150 "<u>Artificial Intelligence for Pavement Condition</u> <u>Assessment from 2D/3D Surface Images</u>"

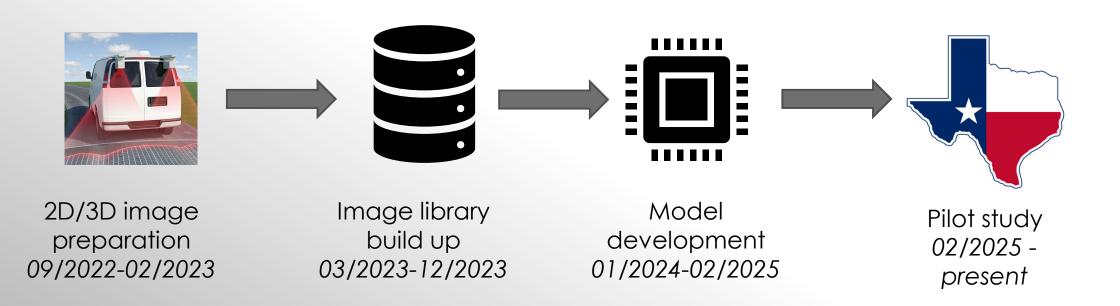
- A real-world Stress Test
 - Texas manages over 200,000 lane miles of highway
 - Multiple pavement types are included: CRCP, JCP, ACP
 - Statewide image data collected by vendor-operated vans
 - a unique opportunity to study model generalization across real-world diversity



PROJECT OVERVIEW



• Technical framework





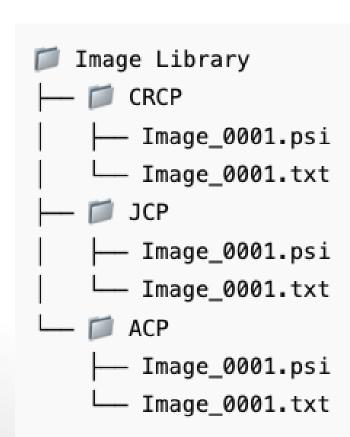
PROJECT OVERVIEW



- Primary goal: explore the capabilities and limitations of Al
 - Focused on evaluating feasibility, reliability, and scope.
- Early observations reveal practical challenges
 - Variability in data quality, surface conditions, and distress interpretation affect detection outcomes.
- key focus: where AI succeeds and where it fails
 - Results will guide future integration strategies and model refinement.



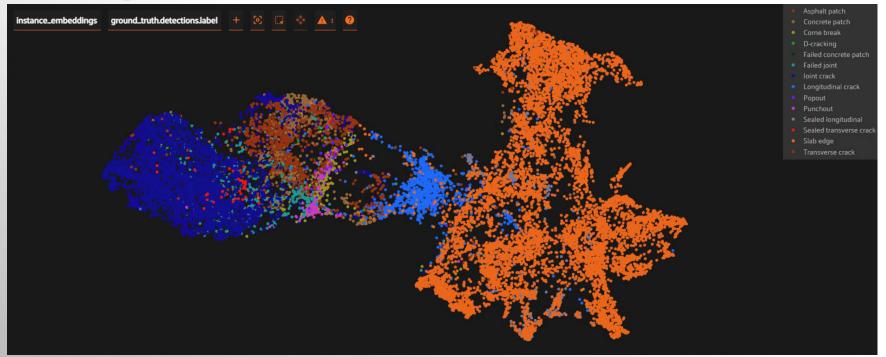
- What is the image library
 - Intensity & range image
 - Pavement types
 - Annotations







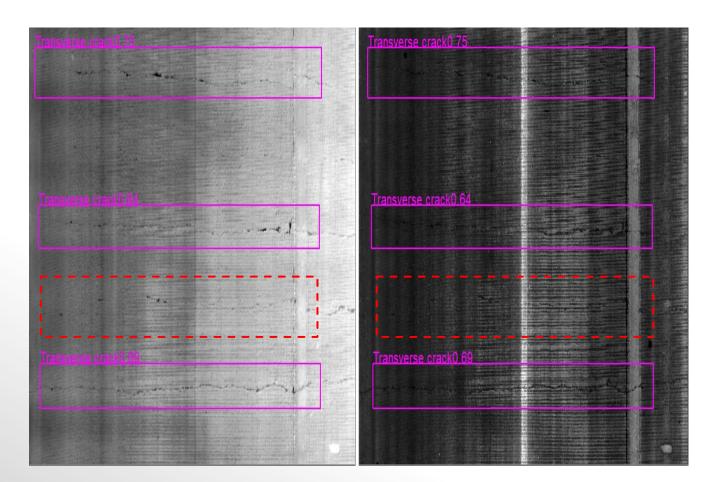
- Data imbalance:
 - Sample imbalance across distress types
 - Further investigation







- Annotation consistency:
 - Subjectivity
 - Annotation Standard
- Impact on model training

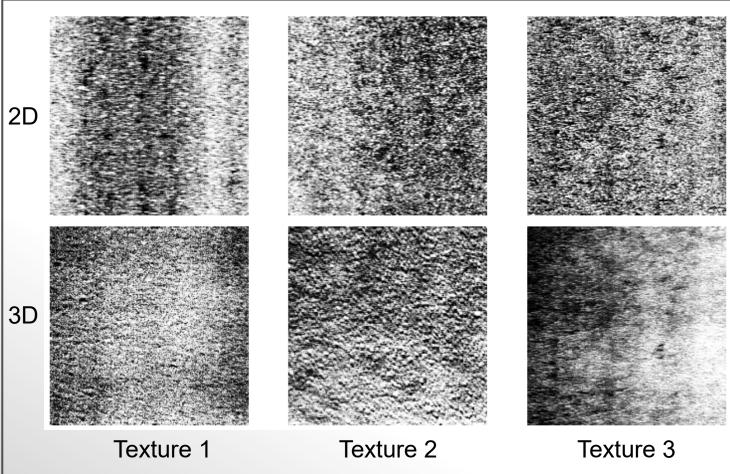




Crack or not crack?



- Diversity coverage:
 - Impossible to cover all scenarios
- Impact on model training
 - Uncertainty over new/unseen data





WHAT DEFINES A HIGH-QUALITY DATASET?

- Representative coverage of real-world condition
- Balanced or intentionally curated class distribution
- Consistent and reliable annotation
- Sufficient quantity with verified quality





- Common model Failures:
 - Misclassification
 - Missed detection
 - Hallucination





- Misclassification:
 - Distress detected, but assigned wrong class
 - Label inconsistency
 - Domain shift
- How to mitigate:
 - Annotation check and model retrain
 - Complementary data collection



- Missed Detection:
 - Rare, subtle, or degraded features
 - Model's limited exposure to edge cases
 - Domain shift
- How to mitigate:
 - Complementary data collection



- Hallucination:
 - Mode predicts distress none exists
 - Noise, low-contrast regions
 - Domain shift
- How to mitigate:
 - Negative sample
 - Complementary data collection



FUTURE DIRECTION



- Continuous Improvement Loop
 - Complimentary data collection
 - \circ Field feedback \rightarrow retraining \rightarrow better generalization
 - Active learning



ACKNOWLEDGEMENT

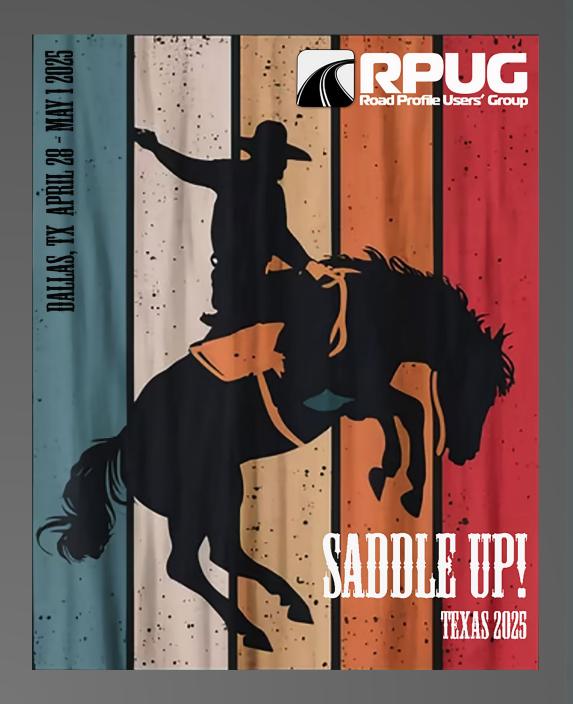


• TxDOT

- For funding, data access, and statewide collaboration
- Special thanks to TxDOT's pavement division and Andy Mergenmeier

- Pathway Services Inc.
 - For providing high-resolution pavement imaging data





THANK YOU!

