NATIONAL ACADEMIES Sciences Engineering Medicine

TRB TRANSPORTATION RESEARCH BOARD

TRB Webinar: Deploying AI Applications for Asset Management

May 3, 2023

2:00 – 3:30 PM

PDH Certification Information

1.5 Professional Development Hours (PDH) – see follow-up email

You must attend the entire webinar.

Questions? Contact Andie Pitchford at TRBwebinar@nas.edu

The Transportation Research Board has met the standards and requirements of the Registered Continuing Education Program. Credit earned on completion of this program will be reported to RCEP at RCEP.net. A certificate of completion will be issued to each participant. As such, it does not include content that may be deemed or construed to be an approval or endorsement by the RCEP.

ENGINEERING RCEP REGISTERED CONTINUING EDUCATION PROGRAM

AICP Credit Information

1.5 American Institute of Certified Planners Certification Maintenance Credits

You must attend the entire webinar

Log into the American Planning Association website to claim your credits

Contact AICP, not TRB, with questions

Purpose Statement

This webinar will share three successful applications of AI projects on asset management. These may help departments of transportation (DOTs) rethink how they manage their assets at scale in the age of AI. Presenters will share how to apply state-of-the-art AI algorithms with a positive return on investment, how to anticipate the pitfalls of these algorithms, and how to improve asset management efficiency.

Learning Objectives

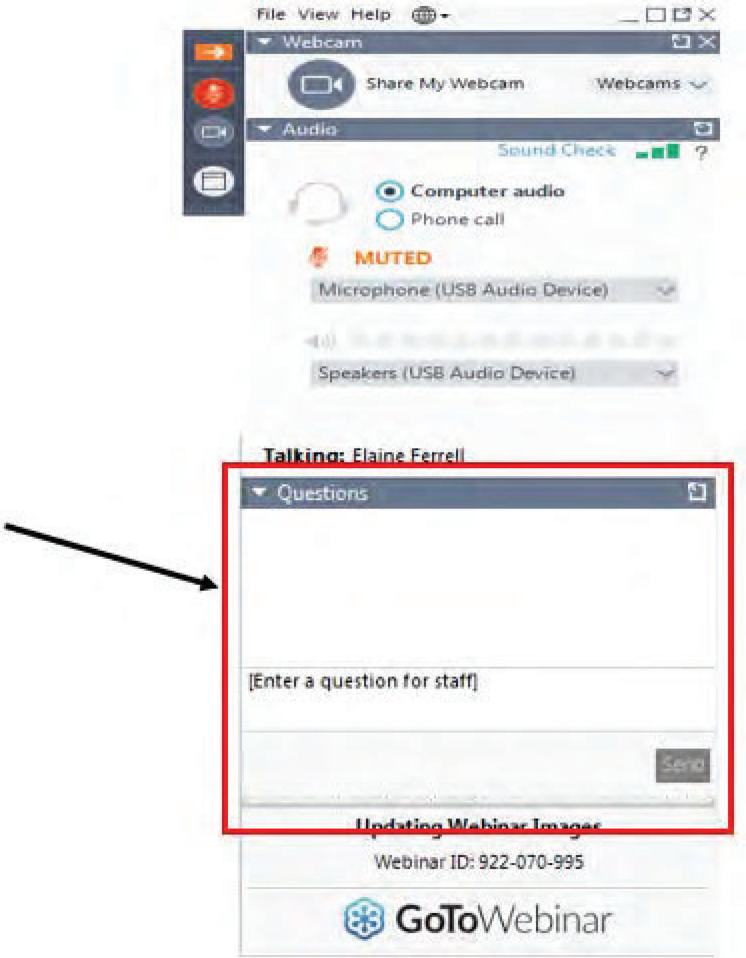
At the end of this webinar, you will be able to:

- Apply state-of-the-art AI algorithms in real-world transportation projects with positive return on investment
- Anticipate deployment pitfalls of using AI algorithms
- Improve asset management efficiency at scale by using AI

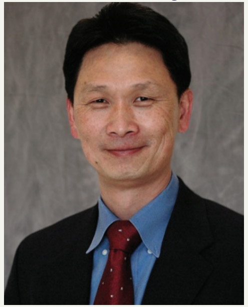
Questions and Answers

- Please type your questions into your webinar control panel

- We will read your questions out loud, and answer as many as time allows



Today's presenters



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TRB Webinar: Deploying AI Applications for Asset Management

Successful AI Applications for Curve Safety Assessment & Compliance, and Pavement Asset Management

Presented by

Yichang (James) Tsai, Ph.D., P.E., Professor
Georgia Institute of Technology
Safe Road Solutions, LLC

May 3, 2023

Outline

- Our Research Team and Focuses
- Application 1 (Safety): MUTCD Curve Sign Compliance Checking Using Low-cost Mobile Devices and AI
- Application 2 (Infrastructure): Automated Pavement Condition Evaluation Using 3D Laser Technology and AI
- Summary

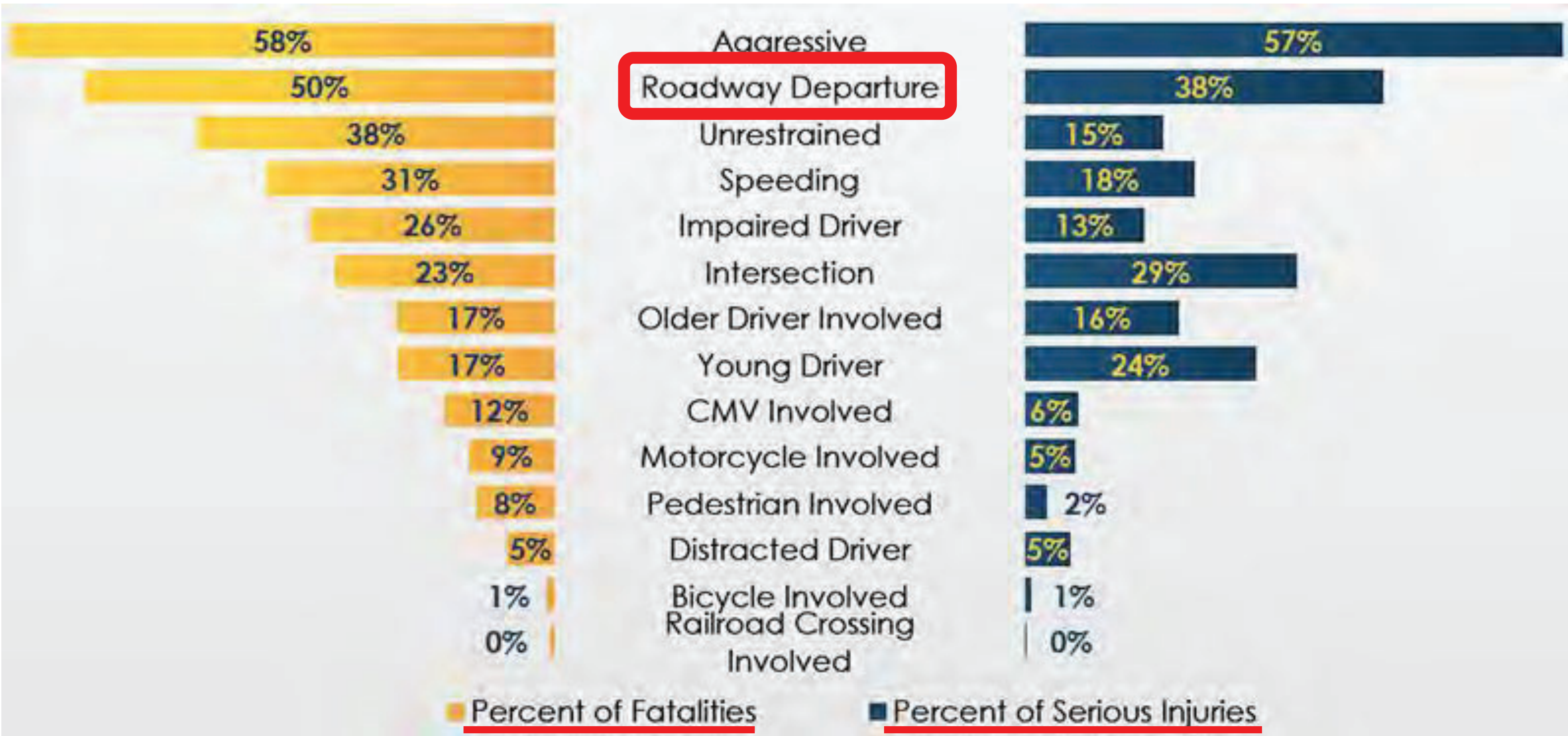
Research Team

- **PhD & MS students at Georgia Tech:**
  - CEE (7): Pingzhou (Lucas) Yu (PhD); Ryan Salameh (PhD); Georgene Geary (PhD); April Gadsby (PhD); Zhongyu Yang (PhD); Ariel Steele (MS); Ronald W Knezevich
  - ECE (4): Yung-An Hsieh (PhD); Chaohan (Huck) Yang (MS); Badr El Hadfidi (MS); Marius M Francois-Marchal (MS); Xinan Zhang (MS)
  - CS (4) & ISYE (1): Anirban Chatterjee (PhD); Nicolas Six (MS); Zhongyu Yang (PhD); Aditya S Tapshalkar; Ben Fan (MS in ISYE)

Application 1 (Safety): MUTCD Curve Sign Compliance Design & Checking Using Low-cost Mobile Devices and AI

Georgia Tech with Safe Road Indicator, LLC

Background - Roadway Departure Fatalities



https://safety.fhwa.dot.gov/tsp/fhwasa19016/

Roadway Departure - Horizontal Curve Safety in the US

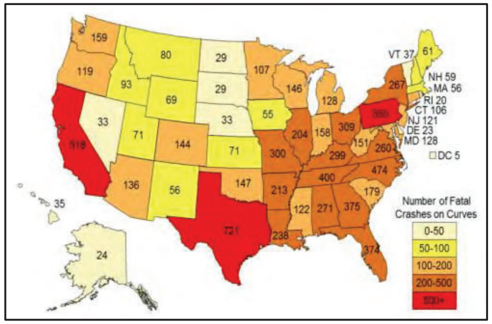
- Horizontal curves play a critical role in roadway safety by providing a smooth transition between tangent sections
- **A disproportionally high number of fatalities occur at horizontal curves (25%)** although **curves only represent a fraction of the roadway network (5%).**

Annual fatalities in the US:

37,206

Annual curve fatalities in the US:

8,767 [2]

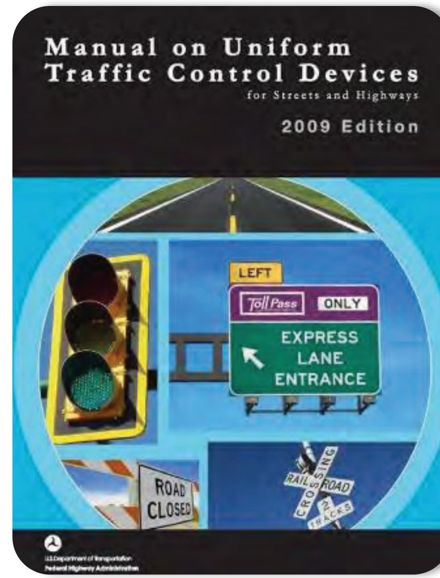


*FHWA. RDs and Curves, 2005-2008.In, FHWA Office of Safety, 2010
Video Source: FHWA

MUTCD Curve Sign Requirement

Enhancements in **curve signage** can have ~ **40% reduction** in **traffic crashes (***CMF ID 1905)*

Regulation



Required to comply with MUTCD to improve roadway safety and to avoid losing **funding and to m**inimize **liabilities**

Advisory Speed Determination

- The Manual on Uniform Traffic Control Devices (MUTCD) provides regulations on the appropriate use of curve warning signs.

- Advisory speed is determined at the speed that does not exceed the maximum side friction.

$$V^2 = 15\,(0.01e + f_{max})\,R$$

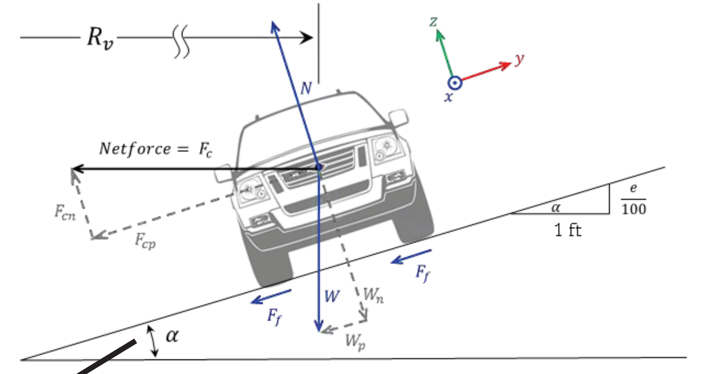
Where,

V = advisory speed, MPH,

f_max = maximum allowed side friction

e = superelevation, %slope,

R = curve radius, ft

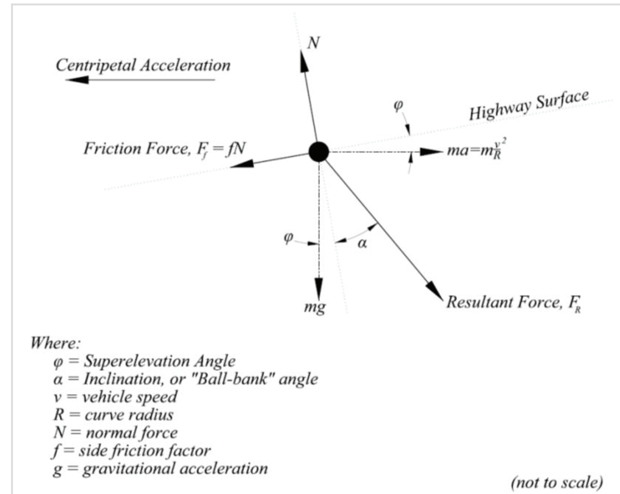


Force diagram

Cross slope/super-elevation

Ball Bank Indicator (BBI) for Determining Adequate Advisory Speed Computation

- A curved level filled with a dampening liquid with a trapped air bubble or "ball" (a digital inclinometer)
  - The geometric degree of the overturning force as a vehicle negotiating a curve
  - A combination of **friction force, super-elevation angle, curve radius, vehicle speed and body-roll angle**



- Installed in a test vehicle with multiple test runs at 5mph increments
- The advisory speed is the highest test speed that does not exceed threshold

Speed	Ball-Bank Threshold		
	2004 AASHTO	2003 MUTCD	2009 MUTCD
≤ 20 mph	14°		16°
25-30 mph	12°	16°	14°
≥ 35 mph	10°		12°
for Truck	-	-	10°

Innovation Need

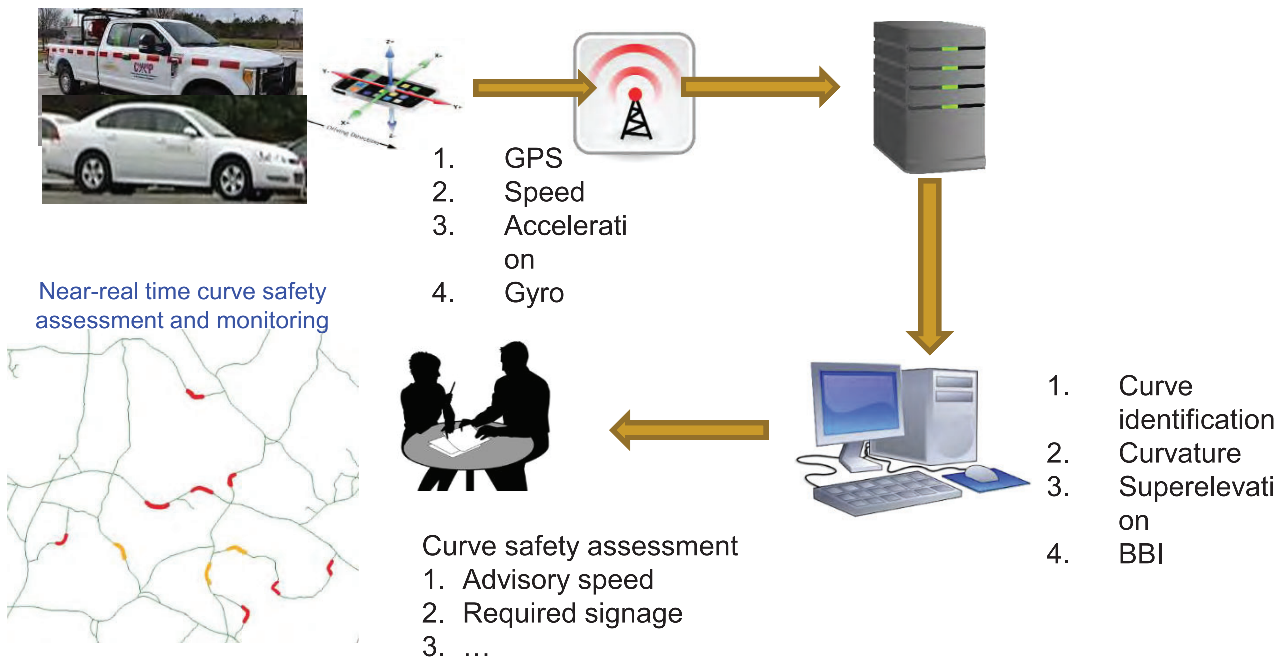
Need for a **timely and continuous safety** assessment of curve site conditions.

Need for a **cost-effective** way for counties and cities with limited resources at network level.

Georgia's Roadway Network
18,000 centerline miles (28,000km)

Proposed Methodology for Live Curve Safety Assessment

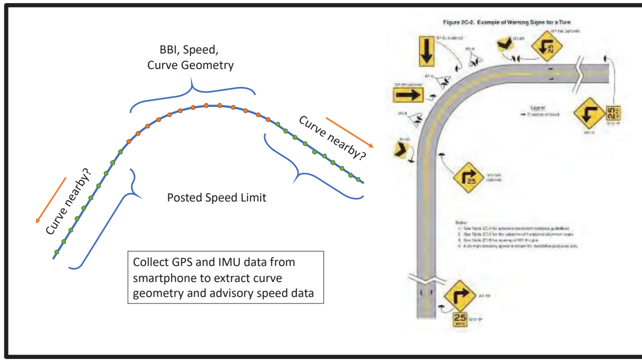
Enable targeted and proactive safety assessment (save money and time for DOTs)



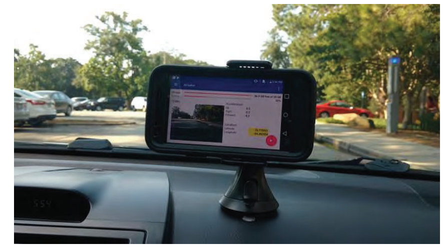
Tsai, Y., Yu, P., Liu, T., Steele, A. (2021) “An Enhanced Network-level Curve Safety Assessment and Monitoring Using Mobile Devices”, National Academy of Science NCHRP Innovation Deserving Exploratory Analysis (IDEA)-214, Final Report

Application Framework

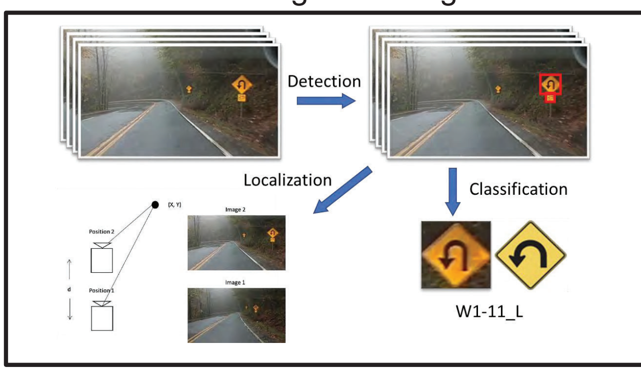
Component #1: Establish Curve Sign Baseline (MUTCD Curve Sign Design)



Data Collection Device: Smartphone Mounted in Vehicles



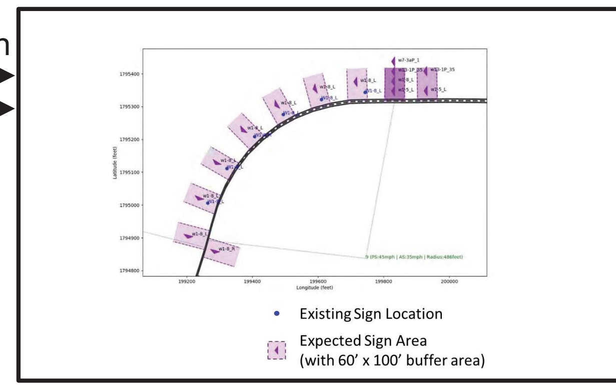
Component #2: Detect Existing Curve Sign



Required Curve Sign

Existing Curve Sign

Component #3: MUTCD Curve Sign Compliance Analysis



A <u>Timely</u>, <u>Low Cost</u>, and <u>Scalable</u> way to analyze curve warning sign compliance

Data Collection: Mobile Devices

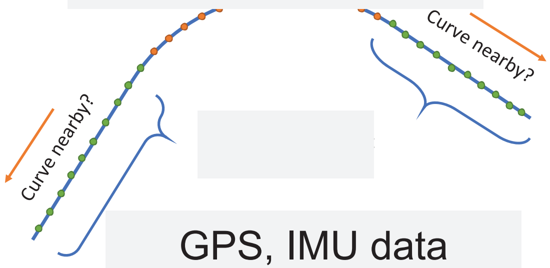
Ball bank indicator (BBI) to compute advisory app

Data collection devices used in research

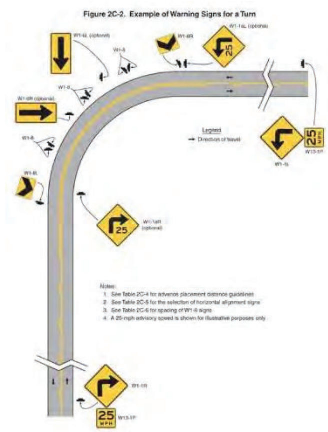
A Timely, Low Cost, and Scalable way to analyze curve warning sign compliance

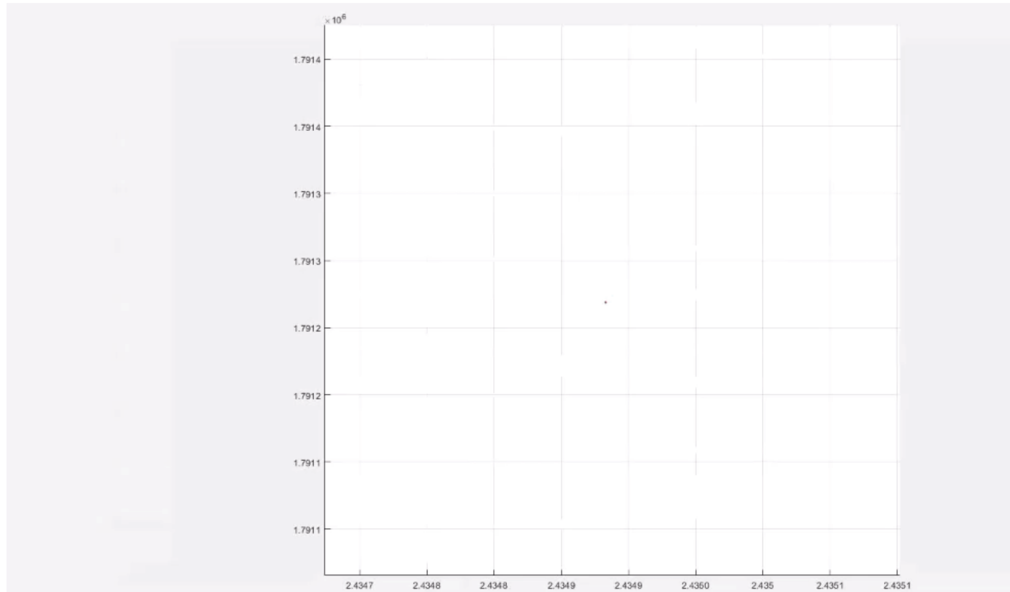
Component #1:
Identify What Curve Signs are Required

BBI, Geometry, Speed



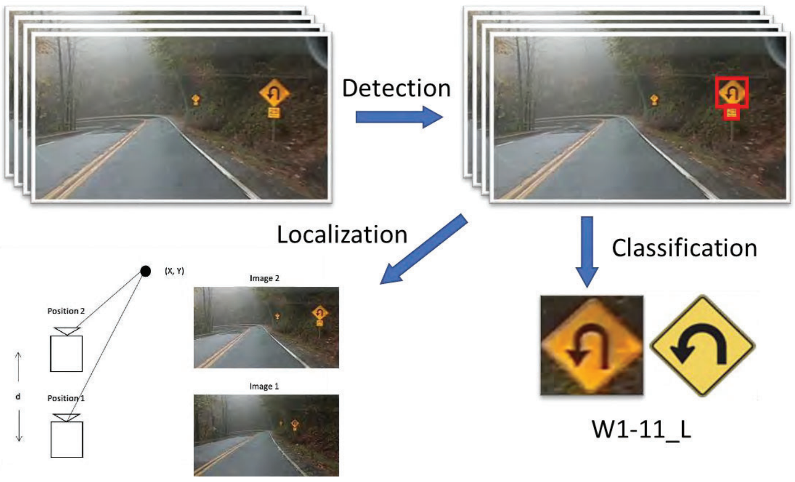
GPS, IMU data collected from smart phone to extract curve geometry and advisory speed





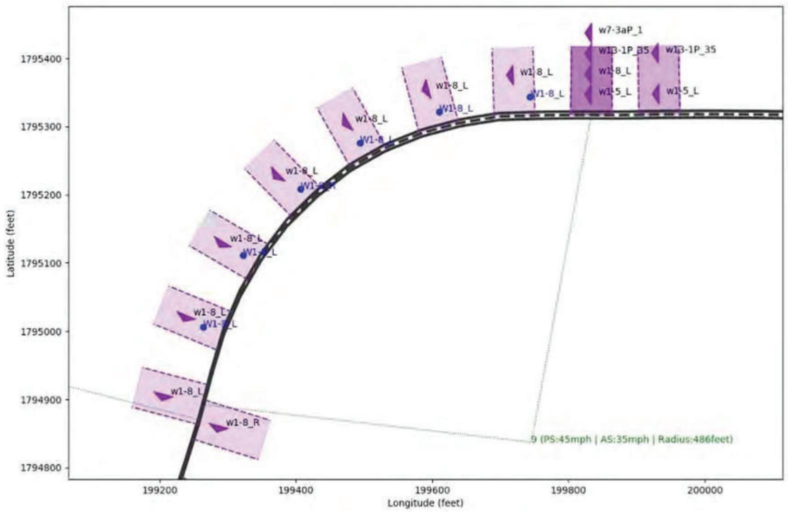
A Timely, Low Cost, and Scalable way to analyze curve warning sign compliance

Component #2:
Detect Existing Curve Sign Inventory



A Timely, Low Cost, and Scalable way to analyze curve warning sign compliance

Component #3:
MUTCD Curve Sign Compliance Analysis

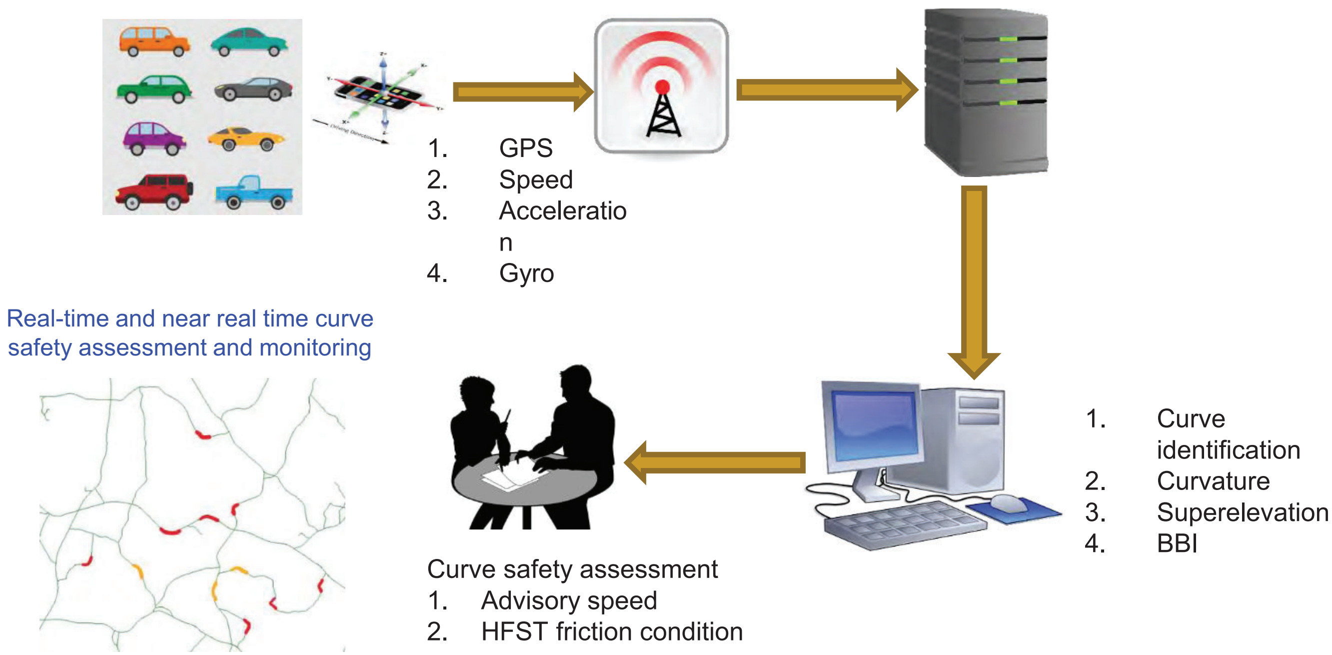


- Existing Sign Location
- Expected Sign Area (with 60' x 100' buffer area)

A Timely, Low Cost, and Scalable way to analyze curve warning sign compliance

Targeted Curve Safety Assessment to Save Time and Money for Proactive Safety Improvement

Transportation agencies can perform **targeted curve safety assessments (say 5% rather than 100% of the network)** and proactive safety countermeasures in a timely manner (daily/weekly rather than yearly).



Using Smartphone Data & Analysis for Safety Improvement Planning & Project Prioritization (e.g. Applications of High Friction Surface Treatment, HFST)

To do next

- **Phase 1: Conduct a pilot study to critically validate the accuracy of the cost-effective solution using low-cost smartphone and AI.**
  - Select one or two counties/cities who are interested in participating in the pilot study to explore new technology
  - Select the test routes with different condition of curves (e.g. different radius, superelevation, grade, etc.).
  - Collect the data on the selected routes using both current commercial products (e.g. Rieker devices) and the Smartphone technology.
  - Compare the difference of the derived advisory speeds and discuss the outcomes
  - Work with participating counties and cities to develop the implementation plan, including data collection, data processing, and reporting
- **Phase 2: Implement the developed cost-effective smartphone solution for counties and cities' curve sign design and MUTCD compliance checking.**

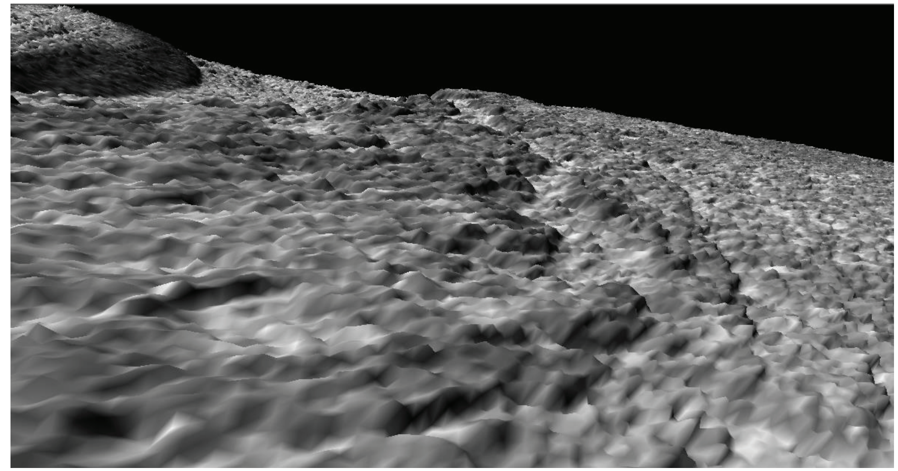
Supported by the NSF I-Corps and Safe Road Solutions, LLC

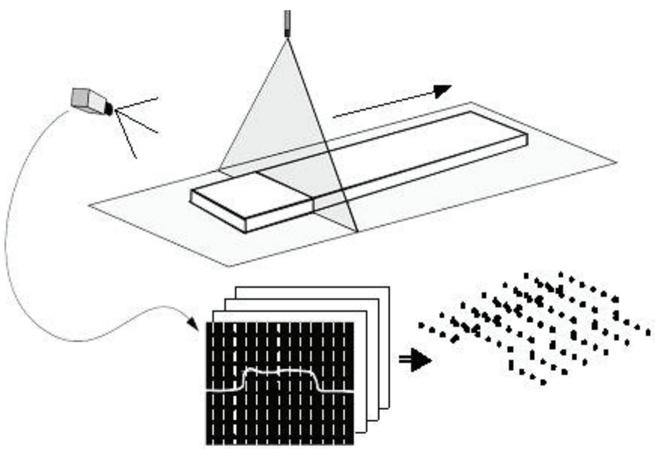
Application 2 (Infrastructure): Automated Pavement Condition Evaluation Using 3D Laser Technology and AI

1. What is 3D Laser technology?
2. Why 3D Laser technology for automated pavement condition evaluation?

Salameh, R., and Tsai, Y. Adoption of 3D Laser Imaging Systems for Automated Pavement Condition Assessment in the United States: Challenges and Opportunities. In Airfield and Highway Pavements 2021 (pp. 219-230).

High-resolution 3D Laser Technology





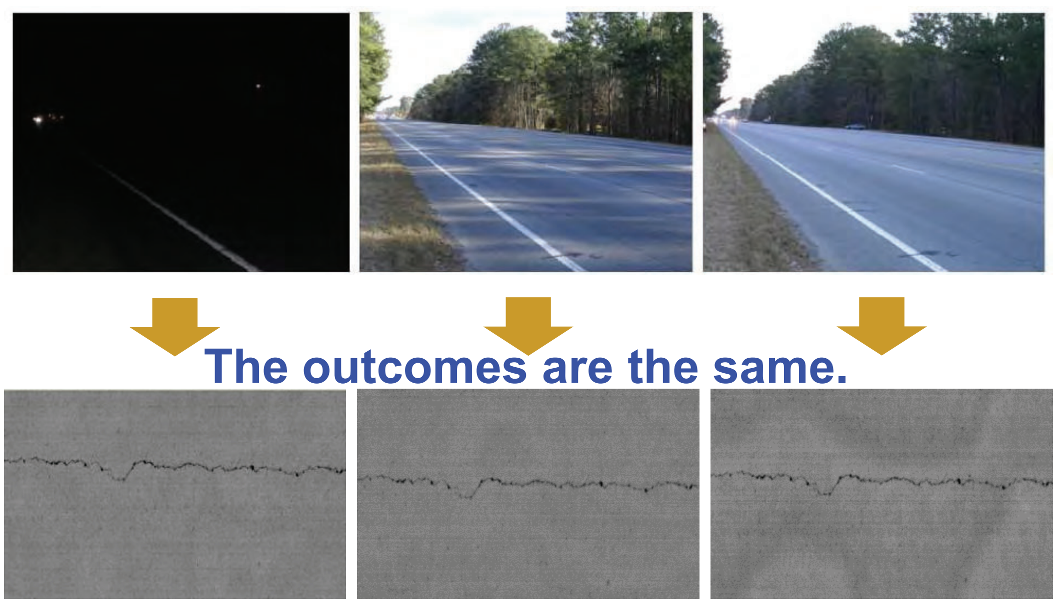
- Resolution
  - Driving direction: 1 – 5 mm
  - Transverse direction: 1 mm
  - Elevation: 0.5 mm
  - Data points collected per second and width covered
    - 2 (lasers) * 2048 (points/profile/laser) * 5600 HZ = 22,937,600 points/second

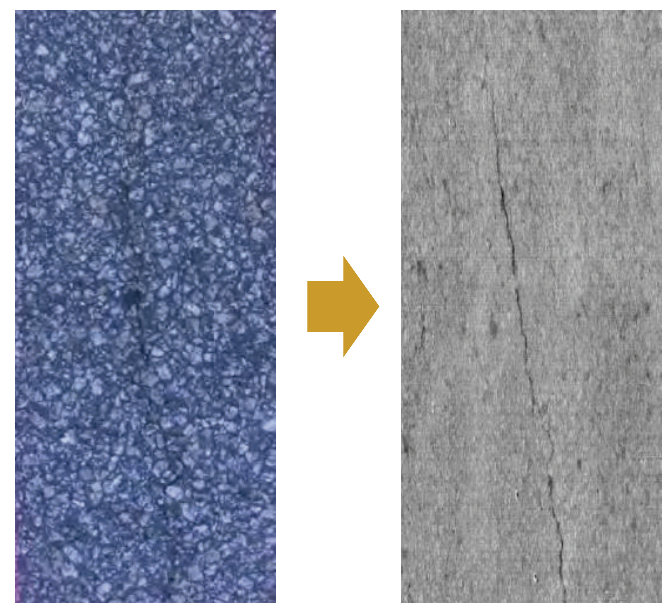
(Laurent, et. al., 2008)

3D Pavement Image for Automated Crack Detection

- 3D pavement images (range images) are not affected by lighting conditions (shadow, day & night) and texture/color contrast
- 3D sensors are becoming a mainstream technology for transportation agencies to collect high-resolution 3D pavement data

Nighttime **Shadow** **Daytime**

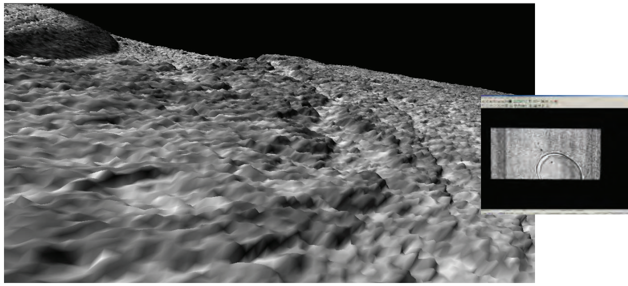




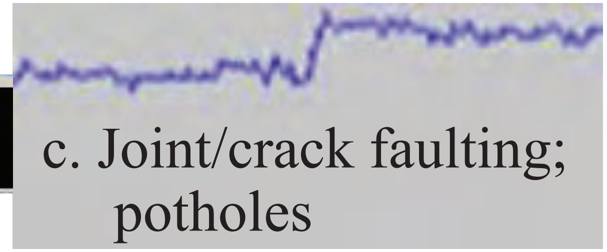
Different lighting conditions **Poor texture contrast**

Automated pavement condition evaluation using 3D laser technology and ML

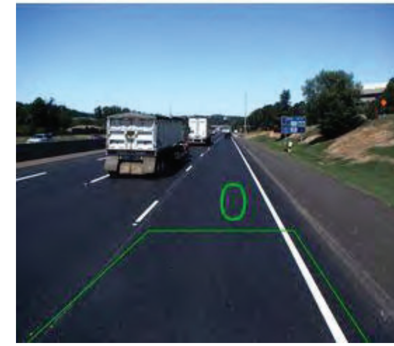
3D pavement data and its applications



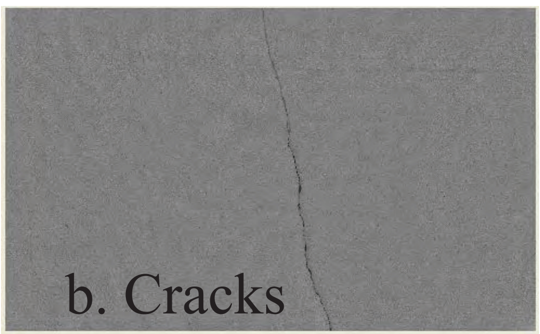
a. Texture (IRI; MPD; RVD)



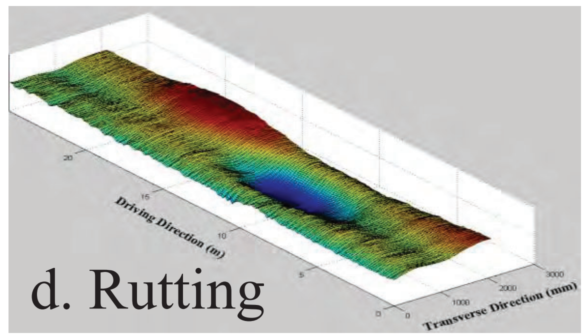
c. Joint/crack faulting; potholes



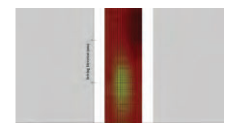
e. Raveling



b. Cracks



d. Rutting



1.Hsieh, Y., Tsai, Y. (2021). “Automated **Asphalt Pavement Raveling Detection and Classification** using Convolutional Neural Network and Macrotexture Analysis”. *Transportation Research Record*. 2021;2675(9):984-994.

3.Hsieh, Y., Tsai, Y. (2020) “**Machine Learning for Crack Detection**: review and model performance comparison”, ASCE Journal of Computing in Civil Engineering, 34 (5), 04020038.

4.Tsai, Y., Chatterjee*, A, (2017) “Pothole Detection and Classification Using 3D Technology and Watershed Method”, ASCE Journal of Computing in Civil Engineering, 32(2), 04017078

5.Tsai, Y., Li*****, F. (2012) “Detecting Asphalt Pavement Cracks under Different Lighting and Low Intensity Contrast Conditions Using Emerging 3D Laser Technology”, ASCE Journal of Transportation Engineering, 138(5), 649–656

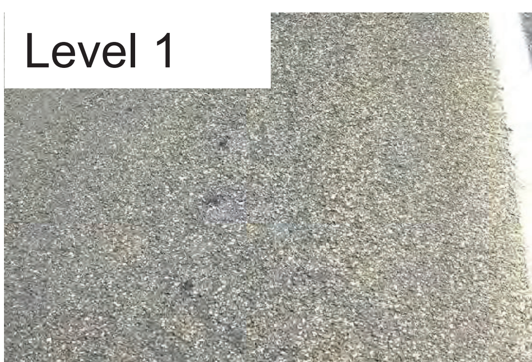
6. Tsai, Y., Wu, Y., Lai, J., Geary, G. (2012) Characterizing Micro-milled Pavement Textures Using RVD for Super-thin Resurfacing on I-95 Using A Road Profiler, Journal of The Transportation Research Record, No.2306, pp.144-150.

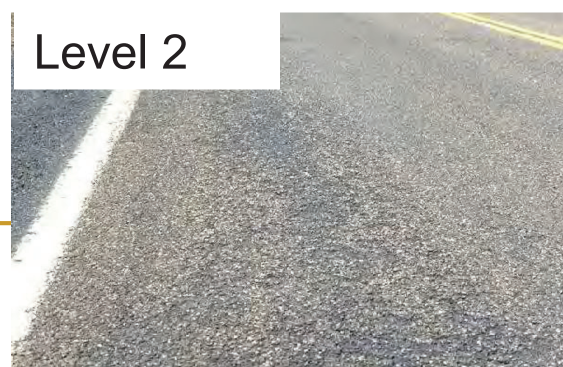
7. Tsai, Y., Wu, Y., Ai, C., Pitts, E. (2012) “Feasibility Study of Measuring Concrete Joint Faulting Using 3D Continuous Pavement Profile Data,” ASCE Journal of Transportation Engineering,138(11),1291-1296.

8. Tsai, Y., Li, F., Wu, Y. (2013) “Rutting Condition Assessment Using Emerging 3D Line-Laser Imaging and GPS/GIS Technologies”, the International Conference on Road and Airfield Pavement Technology, Taipei, Taiwan, July 14, 2013.

Raveling Survey Practices

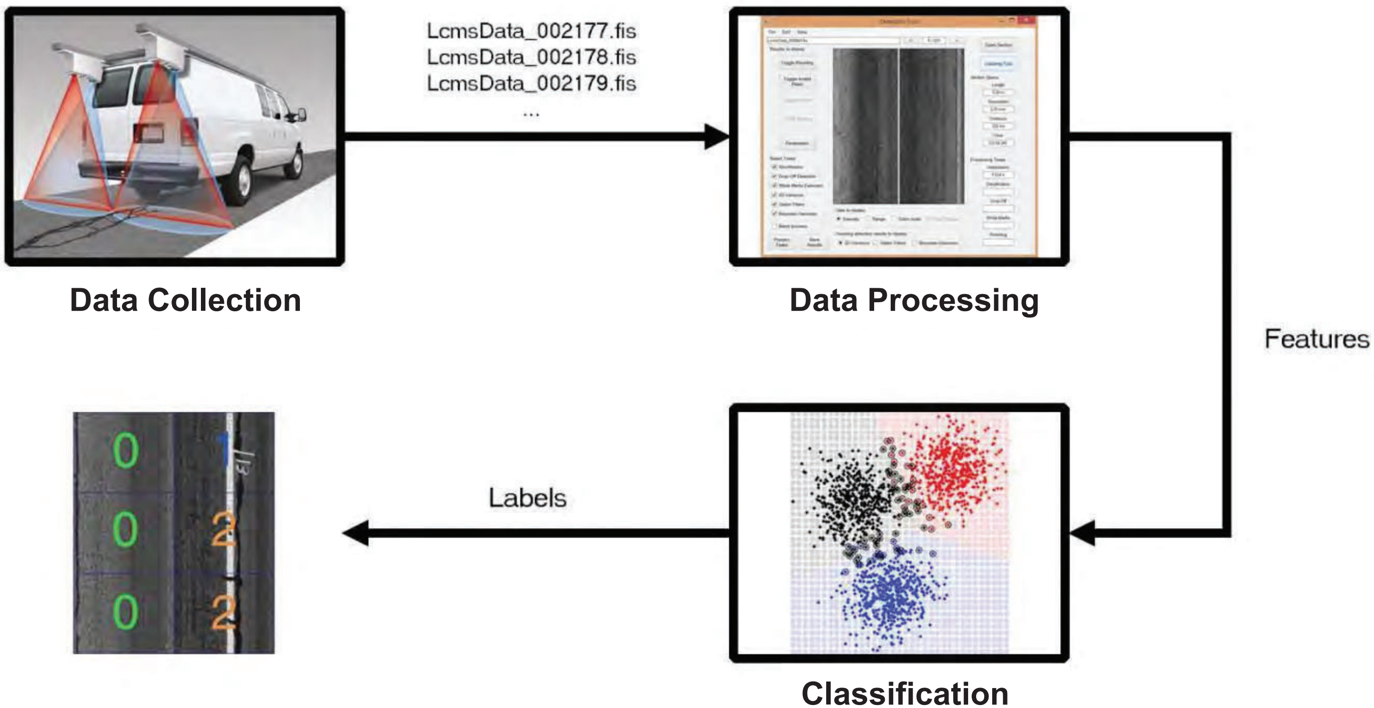
- Classified into 3 severity levels
  - Level 1: Loss of substantial number of stones. Could be rejuvenated with fog seal.
  - Level 2: Loss of most surface. Too many stones lost to rejuvenate the surface and not enough to repave the road.
  - Level 3: Loss of substantial portion of surface layer (>1/2 depth). Surface must be removed and repaved.
- Currently reported by visual inspection
  - Predominant level in % length per mile
- For convenience, in this study, pavements without raveling were labeled as severity level 0.





Automatic Raveling Detection and Classification Using Machine Learning

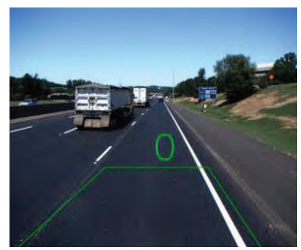
- Procedures
  - Data collection (3D line laser imaging data)
  - Data processing (pre-processing and feature generation)
  - Classification using machine learning, including SVM and Random Forest (output raveling severity levels; classifier needs to be trained first)



Tsai, Y. and Wang Z. (2015) "Development of an Asphalt Pavement Raveling Detection Algorithm Using Emerging 3D Laser Technology and Macrotexture Analysis", National Academy of Science NCHRP IDEA-163 Final Report.

Automatic Raveling Detection and Classification Methods Using 3D Technology and Macro-texture Analysis

(NCHRP IDEA 163)



Tsai, Y. and Wang Z. (2015) “Development of an Asphalt Pavement Raveling Detection Algorithm Using Emerging 3D Laser Technology and Macrotexture Analysis”, National Academy of Science NCHRP IDEA-163 Final Report.

Ten Distress Types (Asphalt Pavements)

Identify/determine
1. Distress type,
2. Severity level,
3. Extent of pavement distress

- 1. Rut Depth
- 2. Load Cracking (Level 1, 2, 3 and 4)
- 3. Block Cracking (Level 1, 2, and 3)
- 4. Reflection Cracking (Level 1, 2, and 3)
- 5. Raveling (Level 1, 2, and 3)
- 6. Edge Distress (Level 1, 2 and 3)
- 7. Bleeding/Flushing (Level 1 and 2)
- 8. Corrugations/Pushing (Level 1, 2 and 3)
- 9. Loss of Section (Level 1, 2 and 3)
- 10. Patches and Potholes

The Florida Department of Transportation (FDOT) has spent more than $1.2 billion dollars annually on only pavement resurfacing.

Automatic Crack Classification

Asphalt Pavement Load Cracking

Level 1	Level 2
Level 3	Level 4

Asphalt Pavement Block Cracking

Level 1	Level 2
Level 3	

Automated Pavement Crack Survey

Automated Data Acquisition

Automated Crack Detection

2D (Intensity) Image

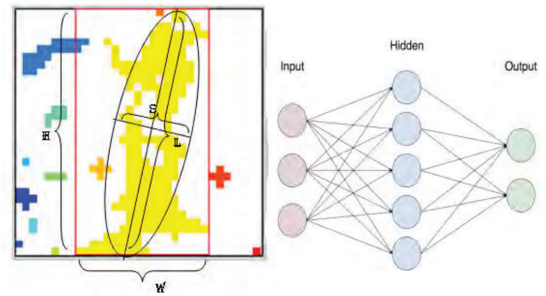
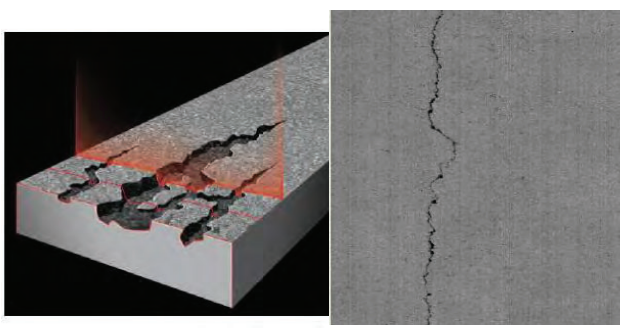
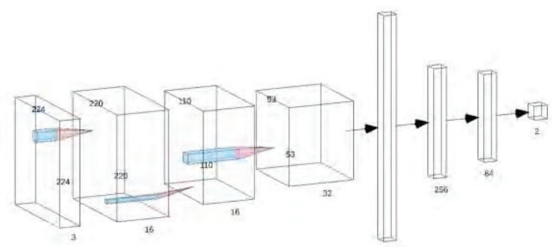


Image proc. & Traditional ML

Emerging Technologies

3D (Range) Image

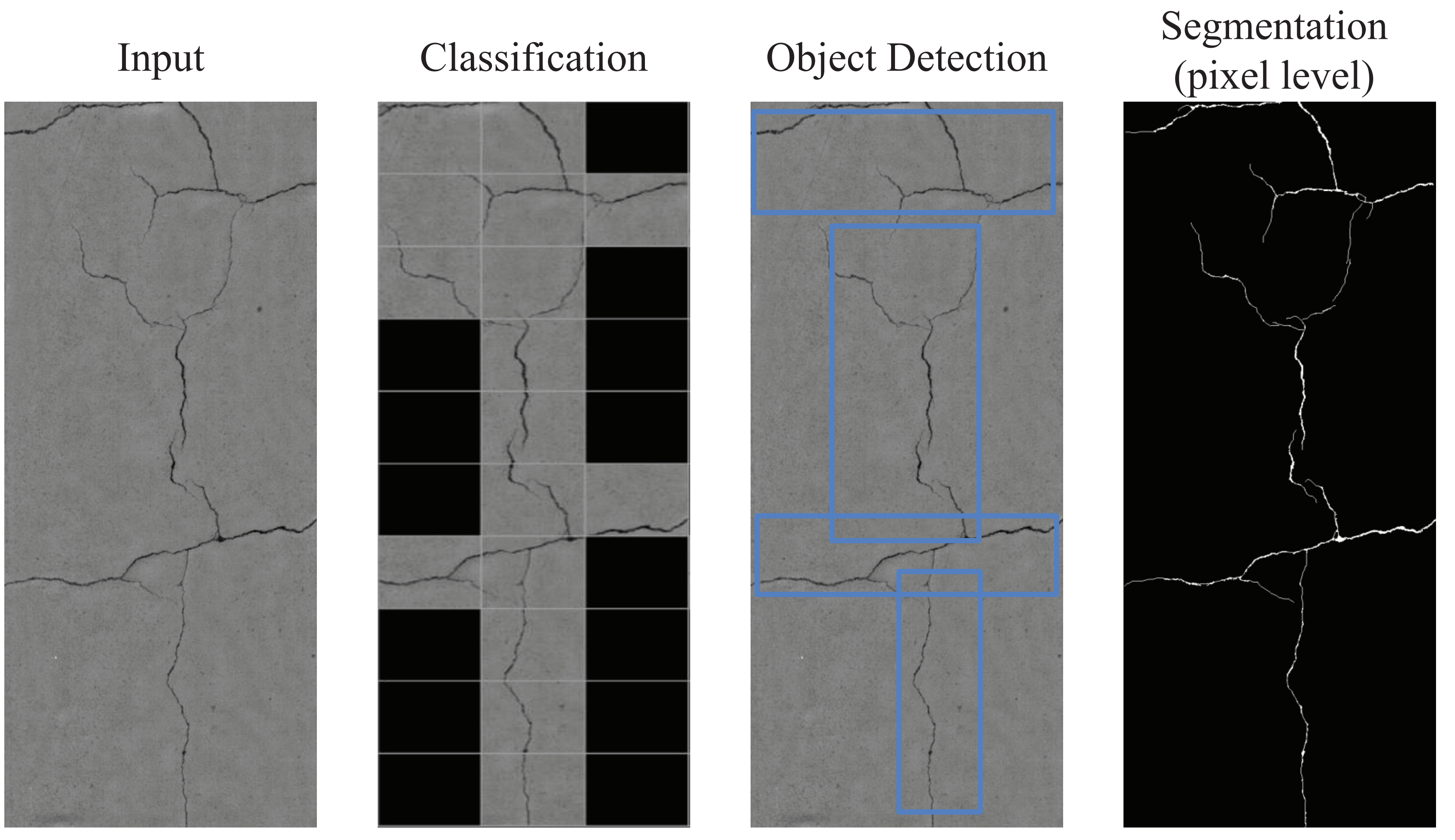




Deep Learning

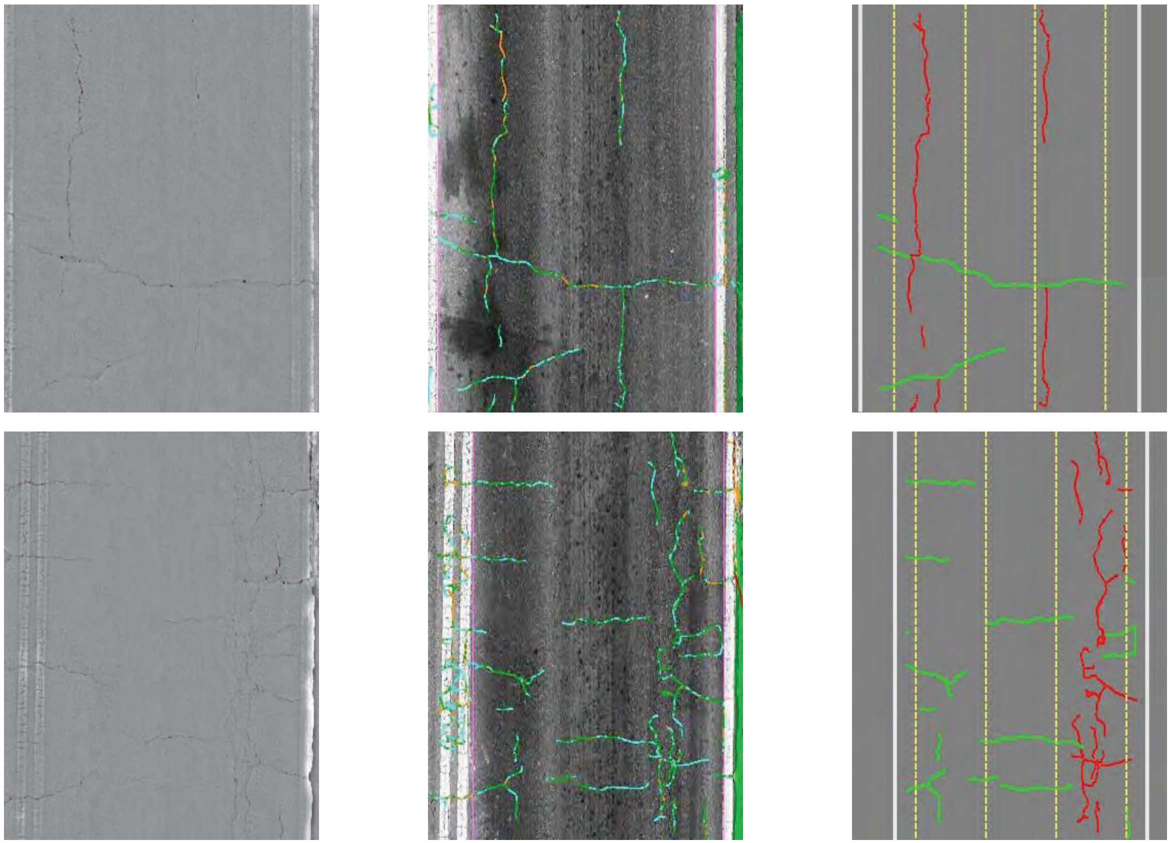
Categories of AI Tasks for Crack Detection

Define the adequate AI Tasks



Hsieh, Y., Tsai, Y. (2020) “Machine Learning for Crack Detection: review and model performance comparison”, ASCE Journal of Computing in Civil Engineering, 34 (5), 04020038.

Load Cracking Classification Results (Severity Level 1-2)



Left Wheelpath
LC Level 1 14.1

Right Wheelpath
LC Level 1 10.1

Non Wheelpath
BT Level 1 17.4

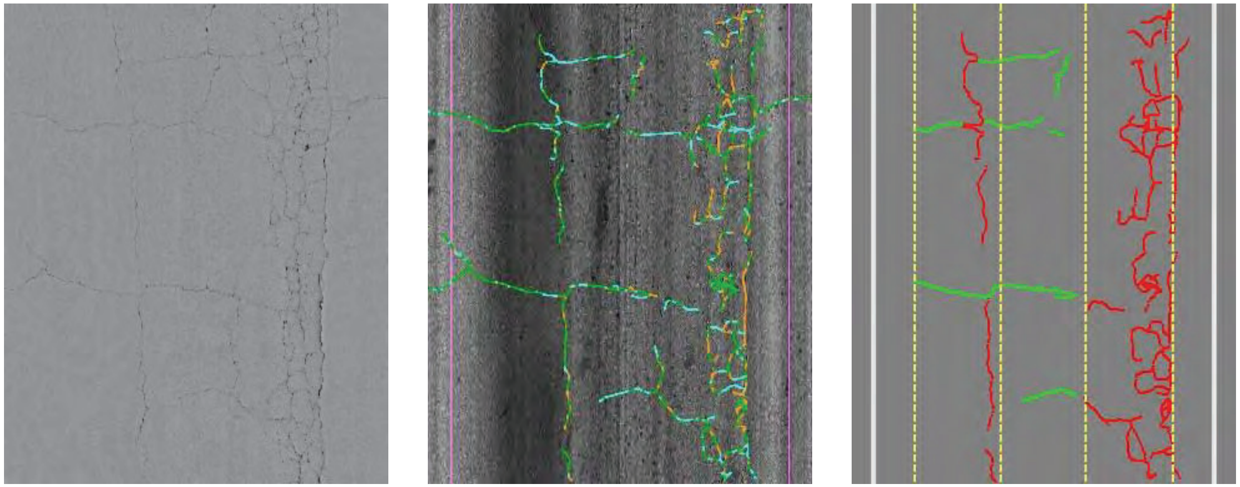
Left Wheelpath
None 0

Right Wheelpath
LC Level 2 16.0

Non Wheelpath
BT Level 1 32.7

Measurement Unit: Foot

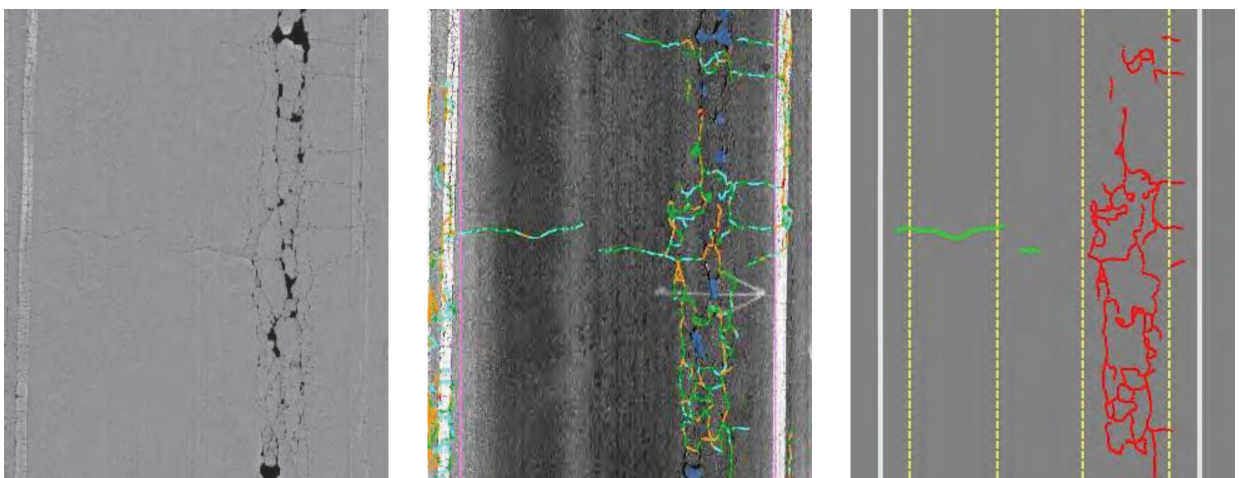
Load Cracking Classification Results (Severity Level 3-4)



Left Wheelpath
LC Level 1 12.6

Right Wheelpath
LC Level 1 15.9

Non Wheelpath
BT Level 1 18.8



Left Wheelpath
None 0

Right Wheelpath
LC Level 2 14.7

Non Wheelpath
BT Level 1 4.1

Measurement Unit: Foot

Successful Implementation of 3D Laser Technology and Automatic Detection and Classification to Georgia's Interstate Highway System

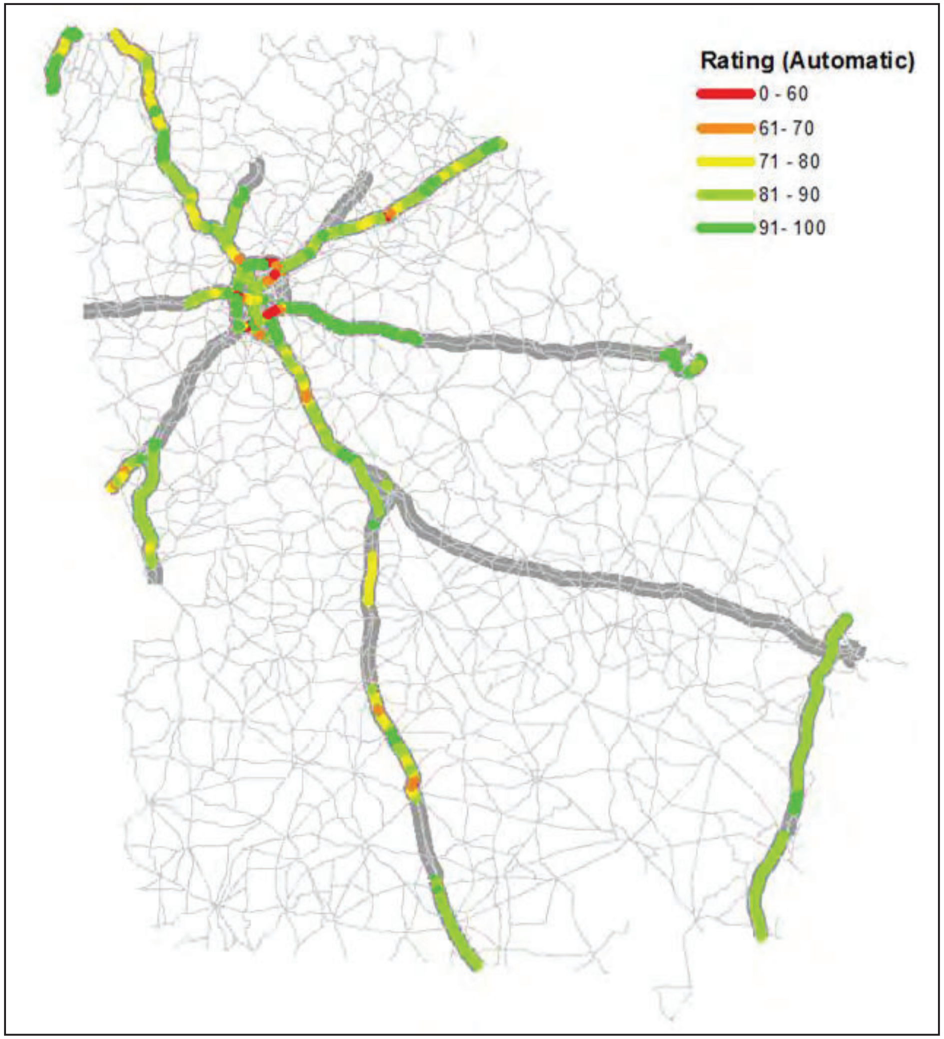
(2017 AASHTO High Research Value Award, Sweet 16)

(Successfully implemented in 1,452.5 survey miles of asphalt pavement condition on Georgia's interstate highway system)

Tsai, Y., Wang, Z., Ai, C. (2017) "Implementation of Automatic Sign Inventory and Pavement Condition Evaluation on Georgia's Interstate Highways", Final Report, Georgia Department of Transportation.

Pavement Condition (COPACES) on Georgia's Interstate Highways

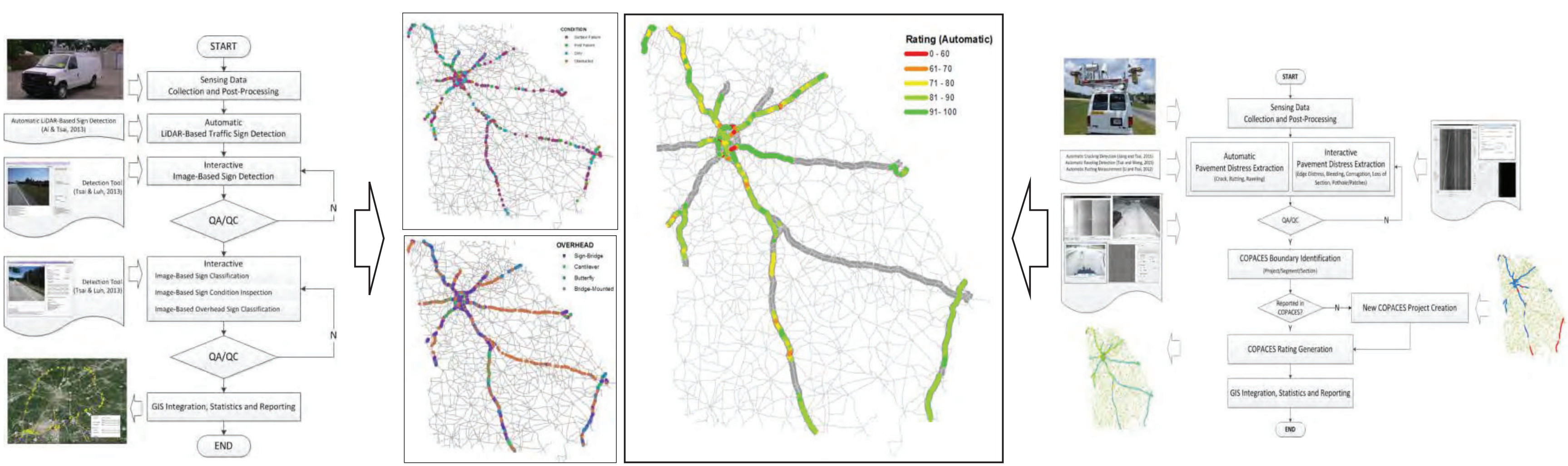
1,452.5 survey miles of asphalt pavement condition on Georgia's interstate highway system



Tsai, Y., Wang, Z., Ai, C. (2017) "Implementation of Automatic Sign Inventory and Pavement Condition Evaluation on Georgia's Interstate Highways", Final Report, Georgia Department of Transportation.

Successful Implementation of Automatic Sign and Pavement Condition Evaluation on Georgia's Interstate Highways

- To implement the automatic traffic sign inventory and pavement distress data collection methods on Georgia's interstate highway system with heavy traffic
- A complete 22,408 sign data and 1452.5 survey miles of asphalt pavement condition on Georgia's interstate highway system



Summary

- **High-resolution 3D pavement data** provides great opportunities to advance the development of sensor-based pavement performance models and pavement maintenance programming:
  - **New, valuable performance indicators,** like crack intersections and polygons, etc., defined in the crack fundamental element (CFE) need to be devised to characterize the detailed pavement distresses.
  - Linkage needs to be established between **new indicators** and the commonly used composite rating, as well as the **optimal treatment method and timing**.
  - **Small-scale, localized treatments (homogeneous pavement condition sections)** can be identified and planned cost effectively using the detailed pavement distress data and the corresponding pavement performance and deterioration models
  - Need for developing the **accurate pavement performance and forecasting models using existing and new indicators**.
  - Need for developing **a new method** to quantify raveling (rather than current qualitative H, M, L severity levels) for supporting the forecasting of optimal timing for fog seal treatment.

Acknowledgements

- Sponsors
  - The Office of the Assistant Secretary for Research and Technology (OST-R) , USDOT
  - NCHRP IDEA program
  - Georgia Department of Transportation

- Research team
  - Research engineers: Dr. Zhaohua Wang and Yiching Wu
  - Previous students: Dr. Feng Li, Dr. Chenglong Jiang, Dr. Chieh Wang, and Dr. Chengbo Ai, Geoffrey Price
  - Current students: Anirban Chatterjee, Georgene Geary, Lauren Gardner and April Gadsby

Thanks
Questions

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Using AI and Machine-vision Technologies in Enforcing Wrong-way Driving Signs

Ken Yang
John Moreno

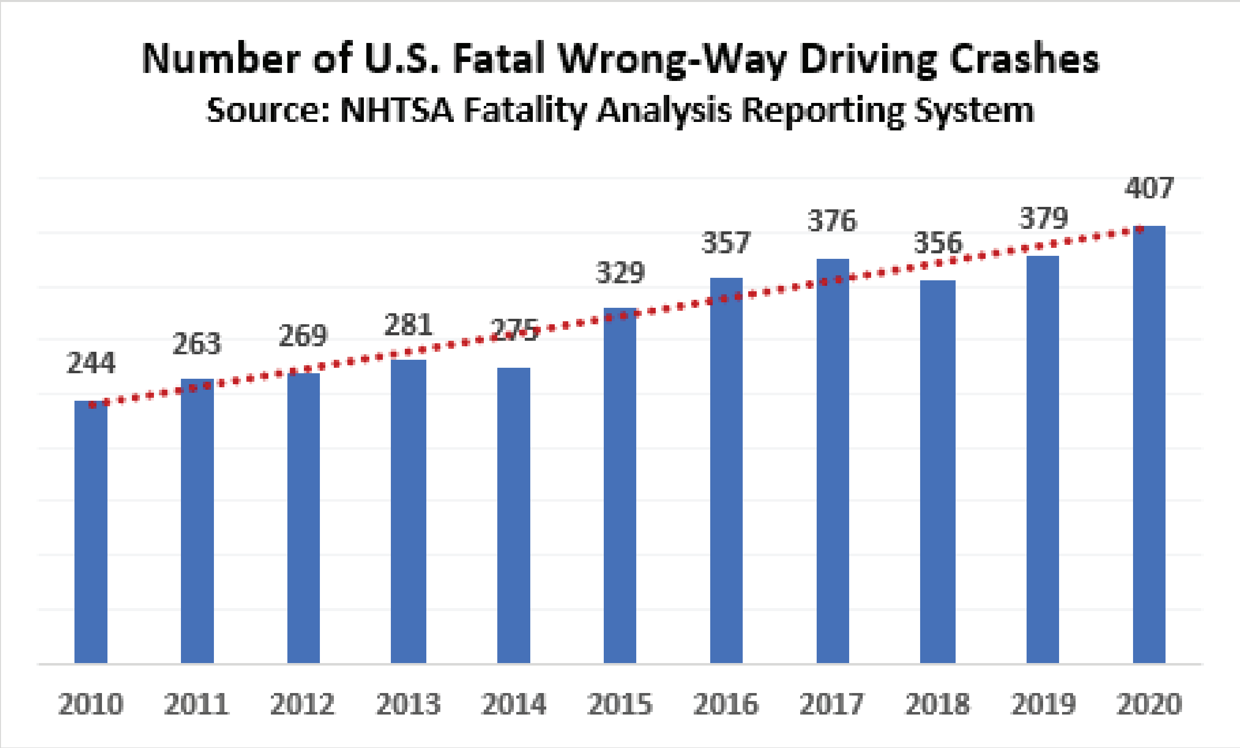
May 3rd, 2023

The Fact of Wrong-way Driving (WWD) Crashes

- Nationally, fatal wrong-way crashes increased 67% from 2010 to 2020

- By comparison, overall crash fatalities increased 33% during the same period.

  - *Richard Retting, senior program officer with the Transportation Research Board*



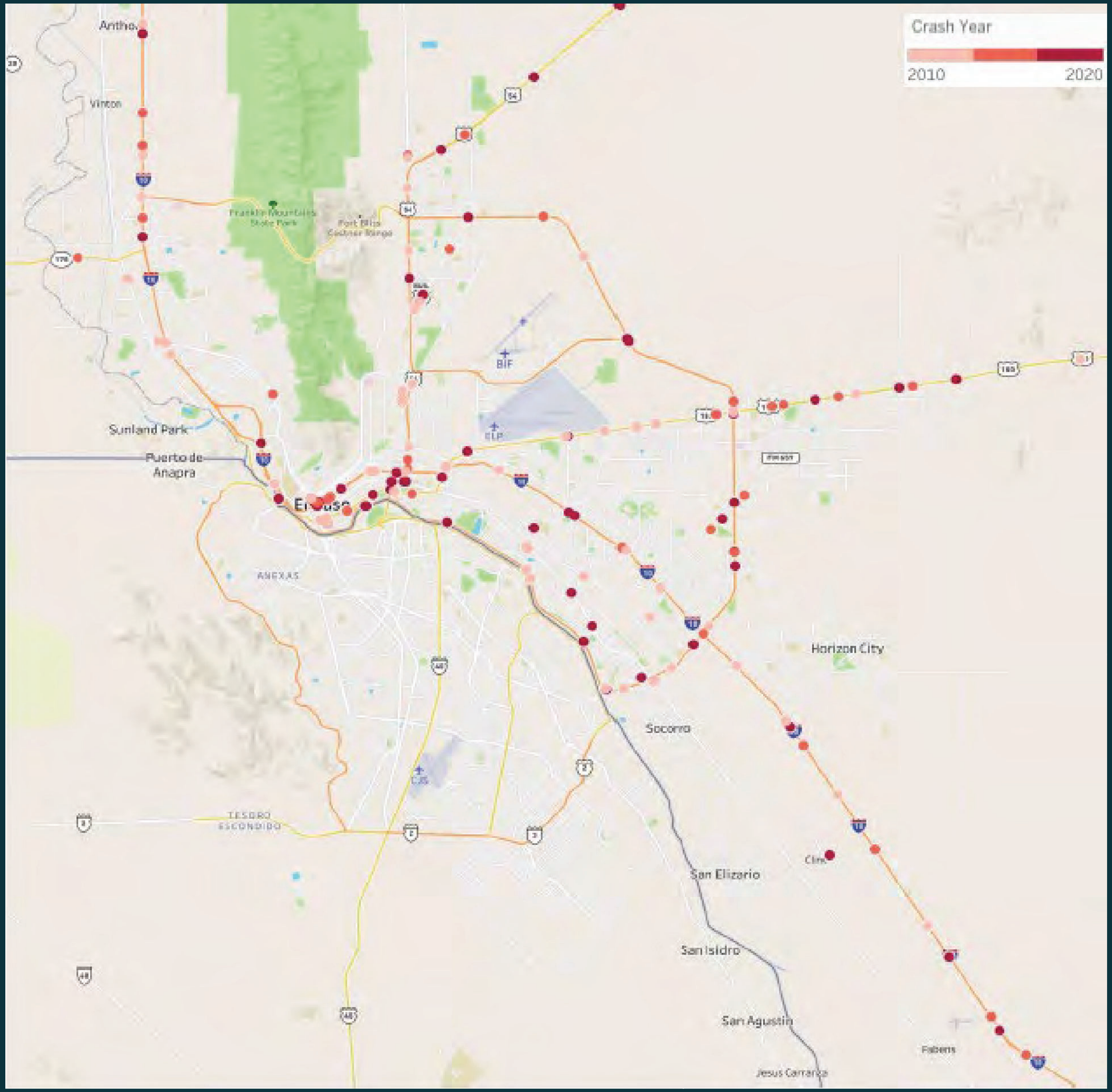
Texas Leads the U.S. in Wrong-Way Crashes

- Texas is also the fifth-highest state in the U.S. in all motor vehicle fatalities.
- According to AAA Texas, the state holds the record for wrong-way auto accidents in the country.
  - Wrong-Way Driving Deaths Rose 34% Nationally, 29% in Texas
  - Out of the 9,560 traffic fatalities nationwide during 2022's first quarter, more than 1,000 of them occurred in Texas
  - 613 people died in wrong-way crashes in 2021, a 15% increase from 2020
- Distracted driving and driving drunk are the biggest contributors to wrong-way crashes in Texas.

Wrong-way Driving Crashes at TxDOT El Paso District

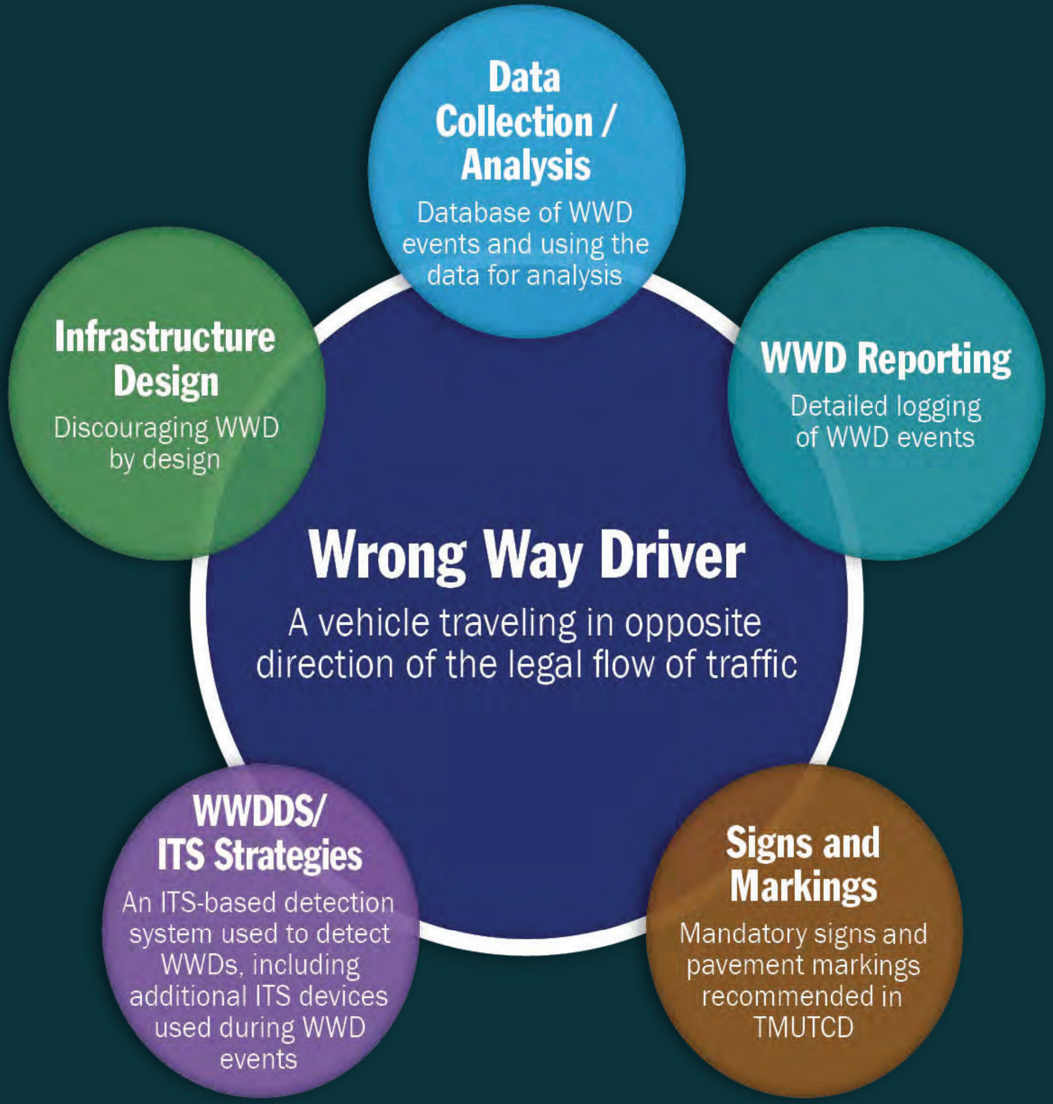
From 2010 to 2019, the TxDOT El Paso District experienced

- 170 wrong-way driving (WWD) related crashes on freeways and TxDOT roadways,
- Resulting in 13 fatalities and more than 70 injuries

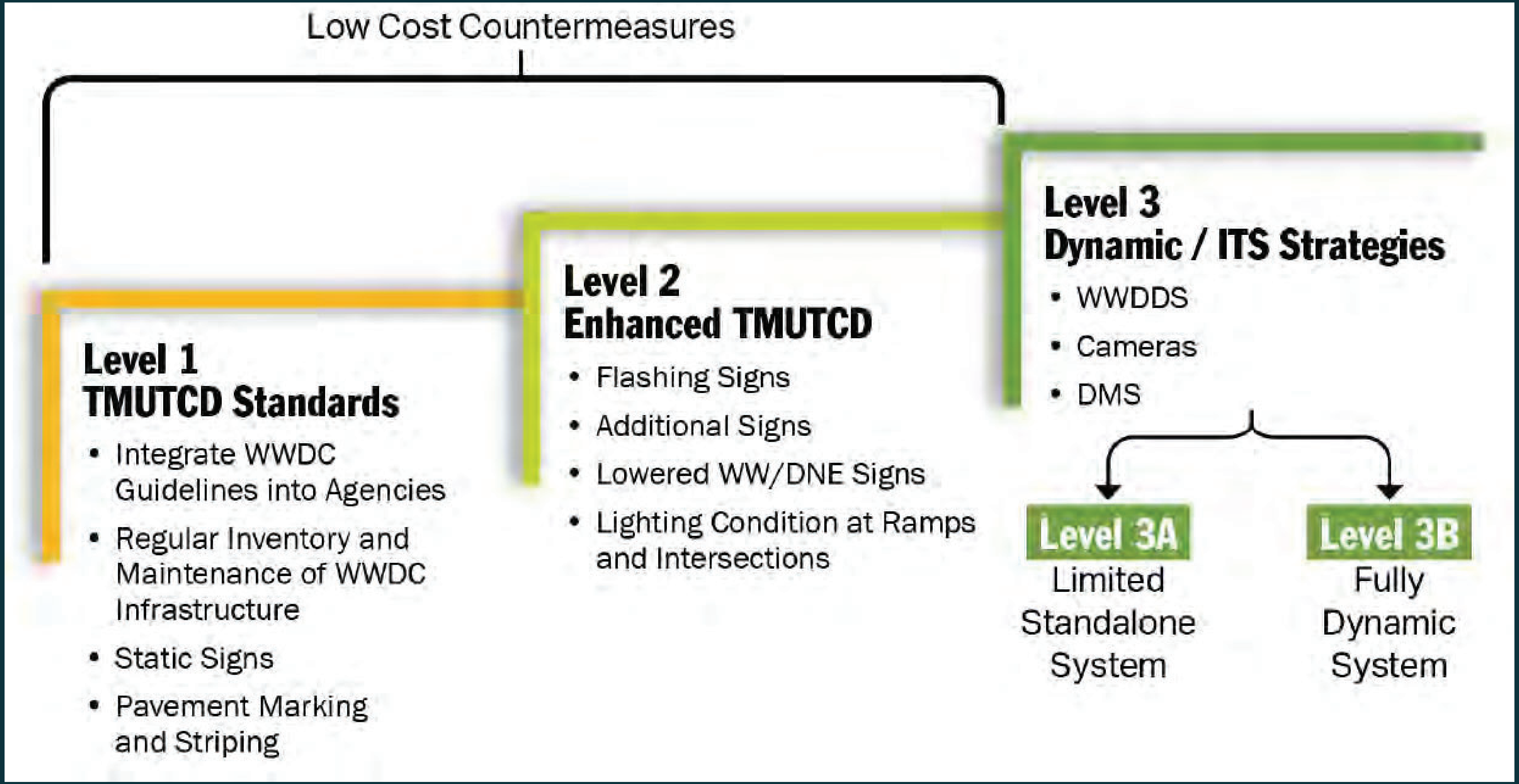


Wrong-Way Driving Universe

- The countermeasures for WWD events are prescribed in three levels
- Each consecutive level being an enhancement over the previous level.
  - **Level 1** - static signage, pavement markings and striping, and other guiding measures as per TMUTCD.
  - **Level 2** - further enhance the effectiveness of Level 1 countermeasures, such as enhanced signage and lighting.
  - **Level 3** - deployment of WWDDS and supporting ITS strategies to prevent, detect and intercept WWD events.



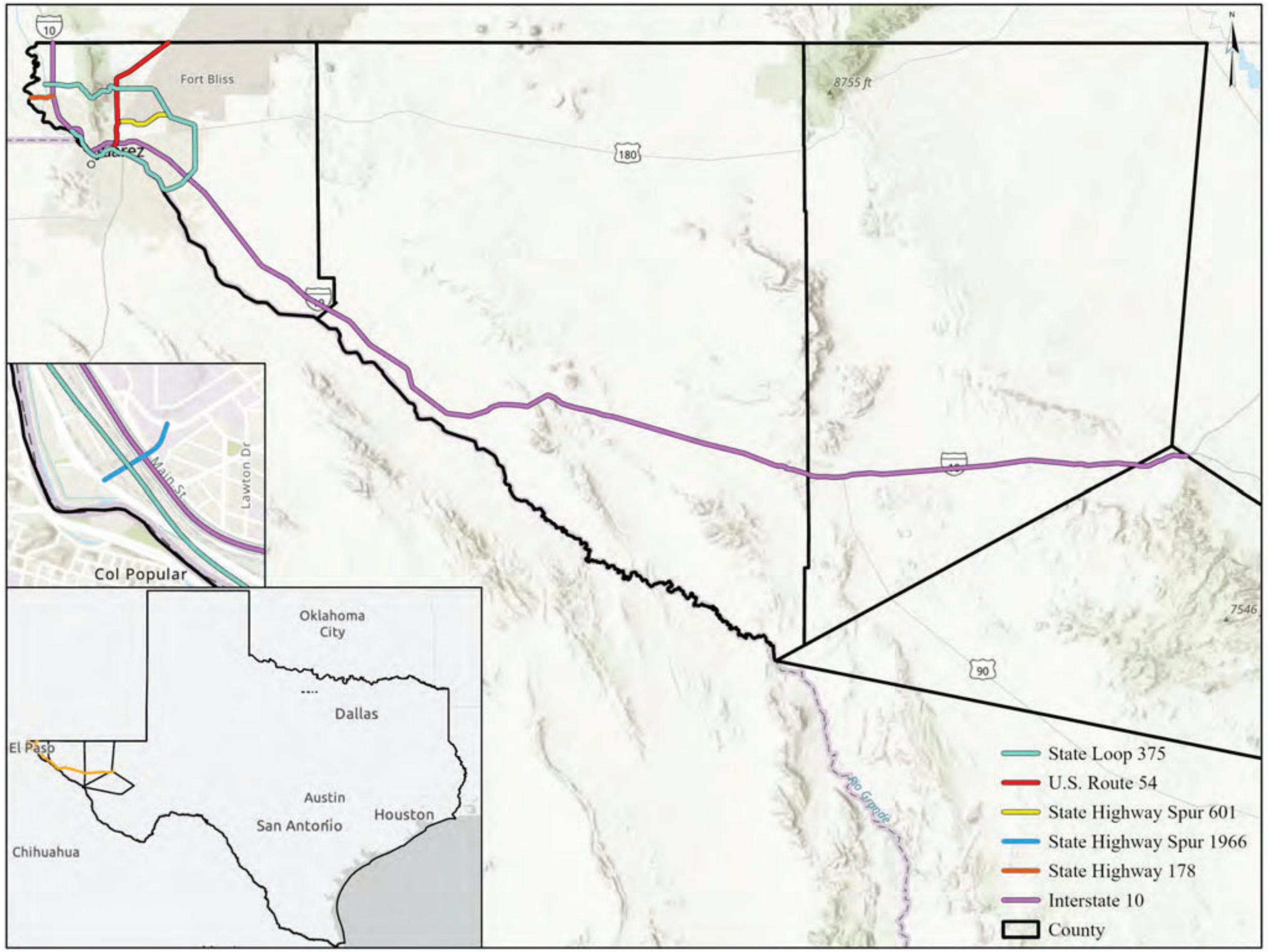
Wrong-Way Driver Countermeasure: Guidelines



Conduct Inventory Survey on Existing WWD Infrastructure Conditions

- WWD Infrastructure Inventory Data Collection along the Roadway

Priority	Roadway	Centerline Miles (Approx.)	WWD Locations (Approx.)
1	Spur 601	8	12
2	US 54	110	32
3	Loop 375	50	70
4	Spur 1966	1	1
5	SH 178	3	5
6	IH 10	190	116
	TOTALS	362	236



Major Signage Types

R5-1

R5-1a


R3-1


R3-2


R3-4

R6-2

R6-1

R1-1

R1-2

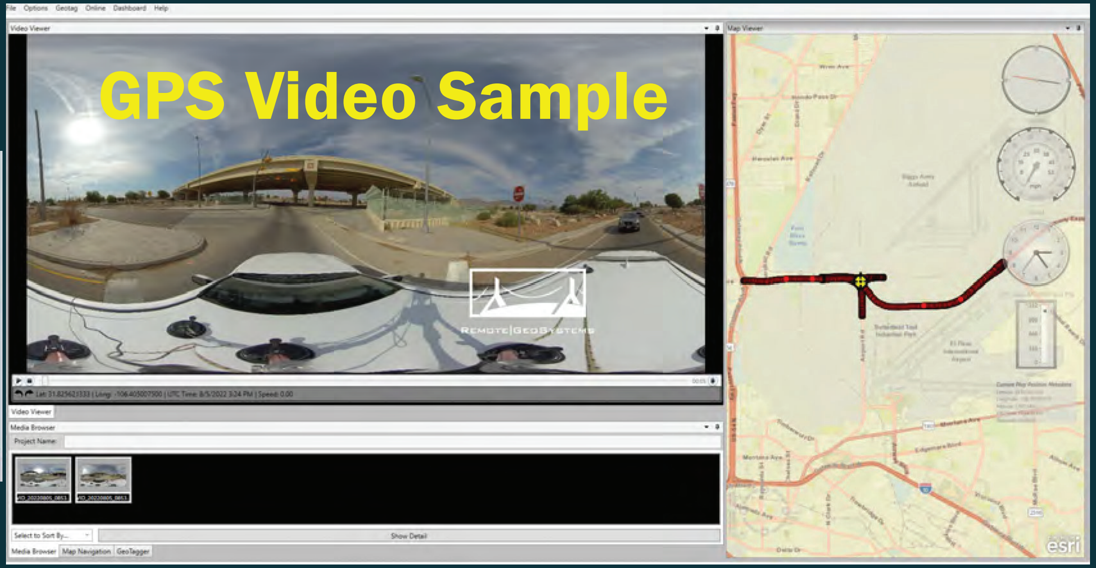
Proposed Methodology of AI-based Data Processing Workflow

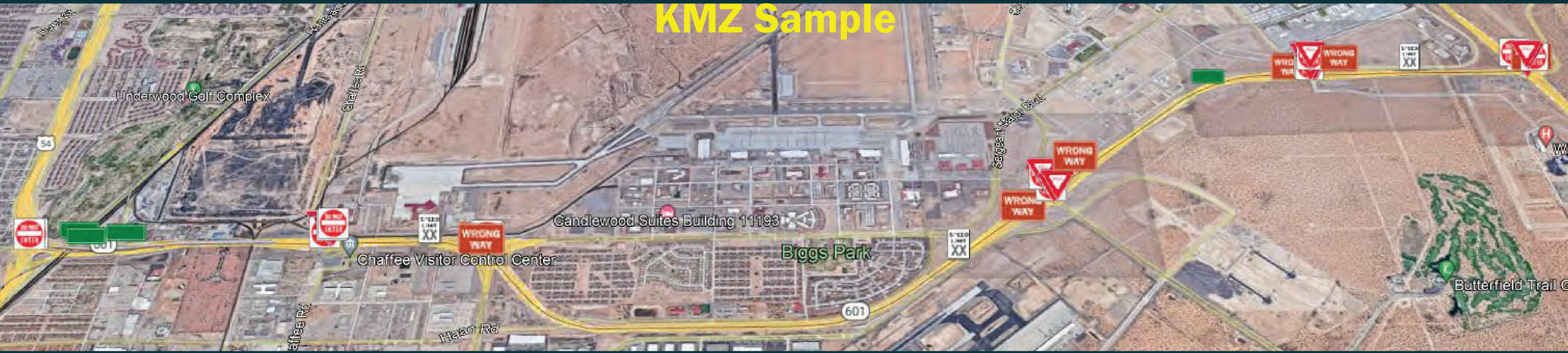
Data Collection and Pre-Processing

WWDC Data Collection:

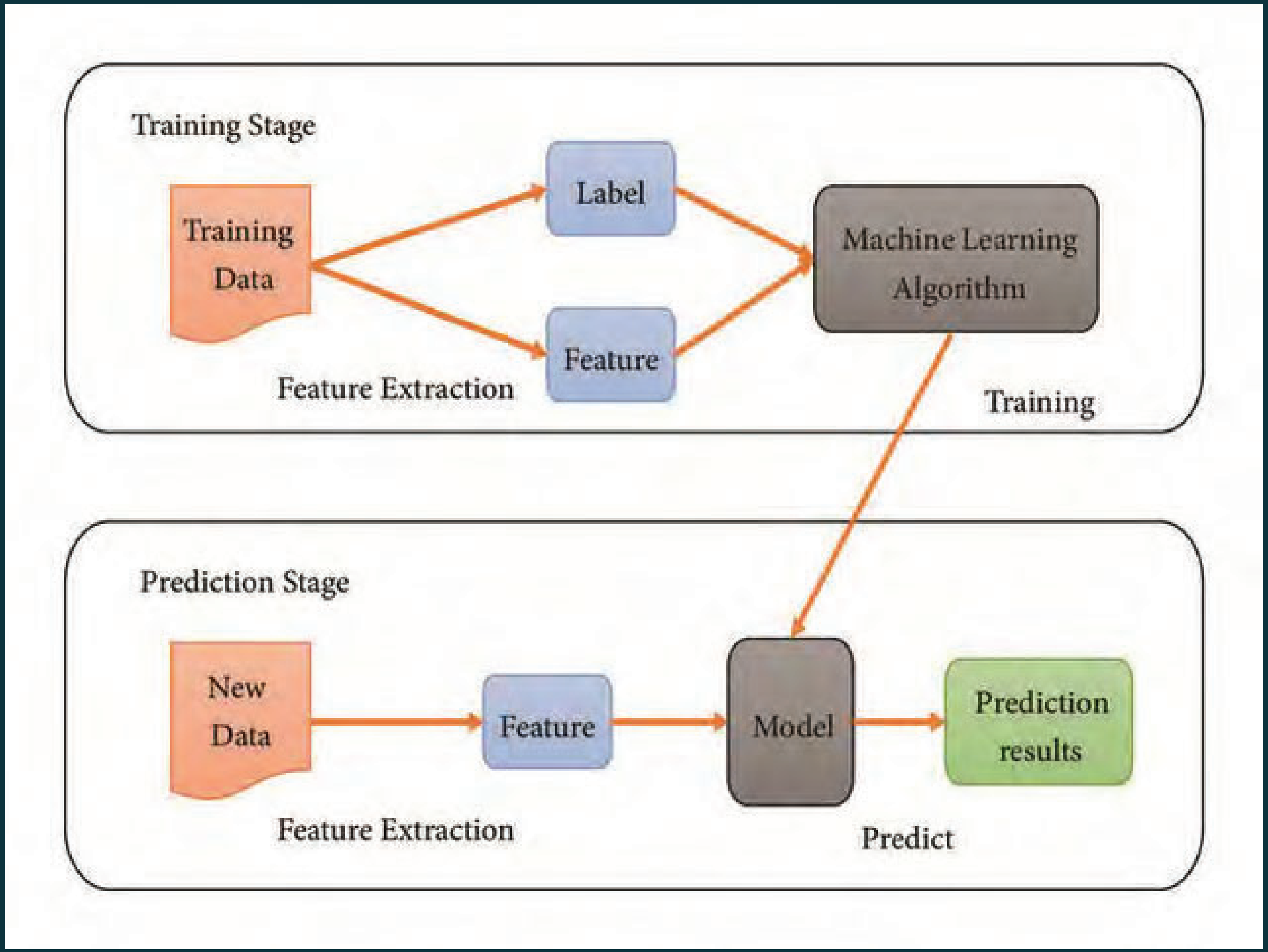
<u>Data Pre-Processing – Items</u>

- ❑ ArcGIS Pro/KMZ
- ❑ GPS Video
- ❑ Excel Summary of Sign Log
- ❖ *QAQC data collection*





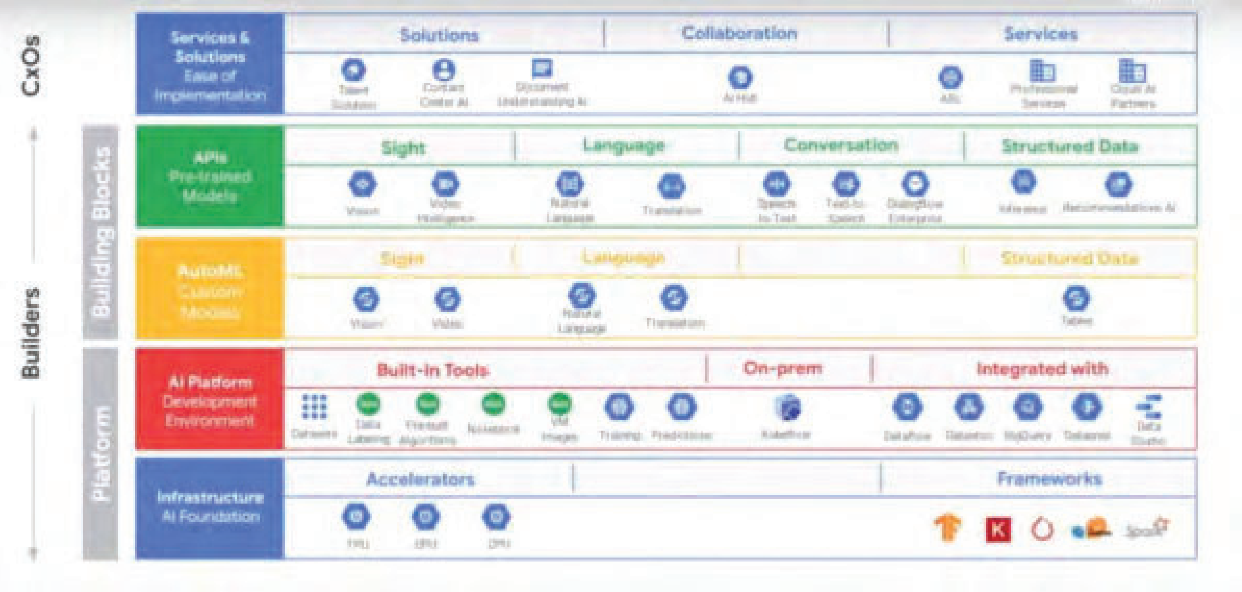
Basic ML Workflow Adopted

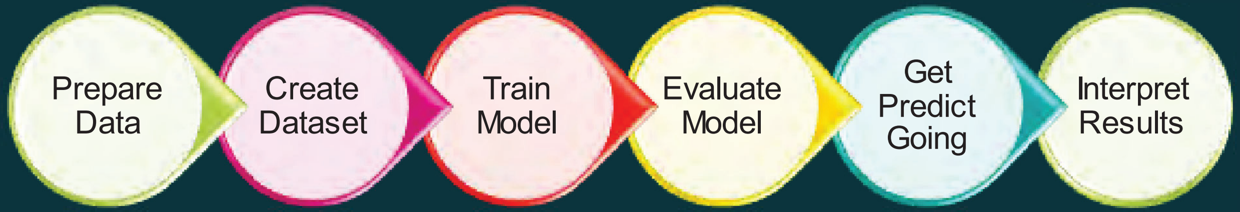


URL: https://www.researchgate.net/publication/332595407_Big_Data_Market_Optimization_Pricing_Model_Based_on_Data_Quality

Google Cloud Platform (GCP) Vertex AI Pipeline

- Provides a way to deploy robust, repeatable machine learning pipelines for the ML workflows.
- Vertex AI – GCP AI platform to use a standard machine learning workflow to train and deploy ML models.
- Vertex AI provides several options for model training
    - **AutoML** - lets you train tabular, image, text, or video data without writing code or preparing data splits.
    - Custom training
- AutoML Video
    - Action Recognition
    - Classification
    - **Object tracking**





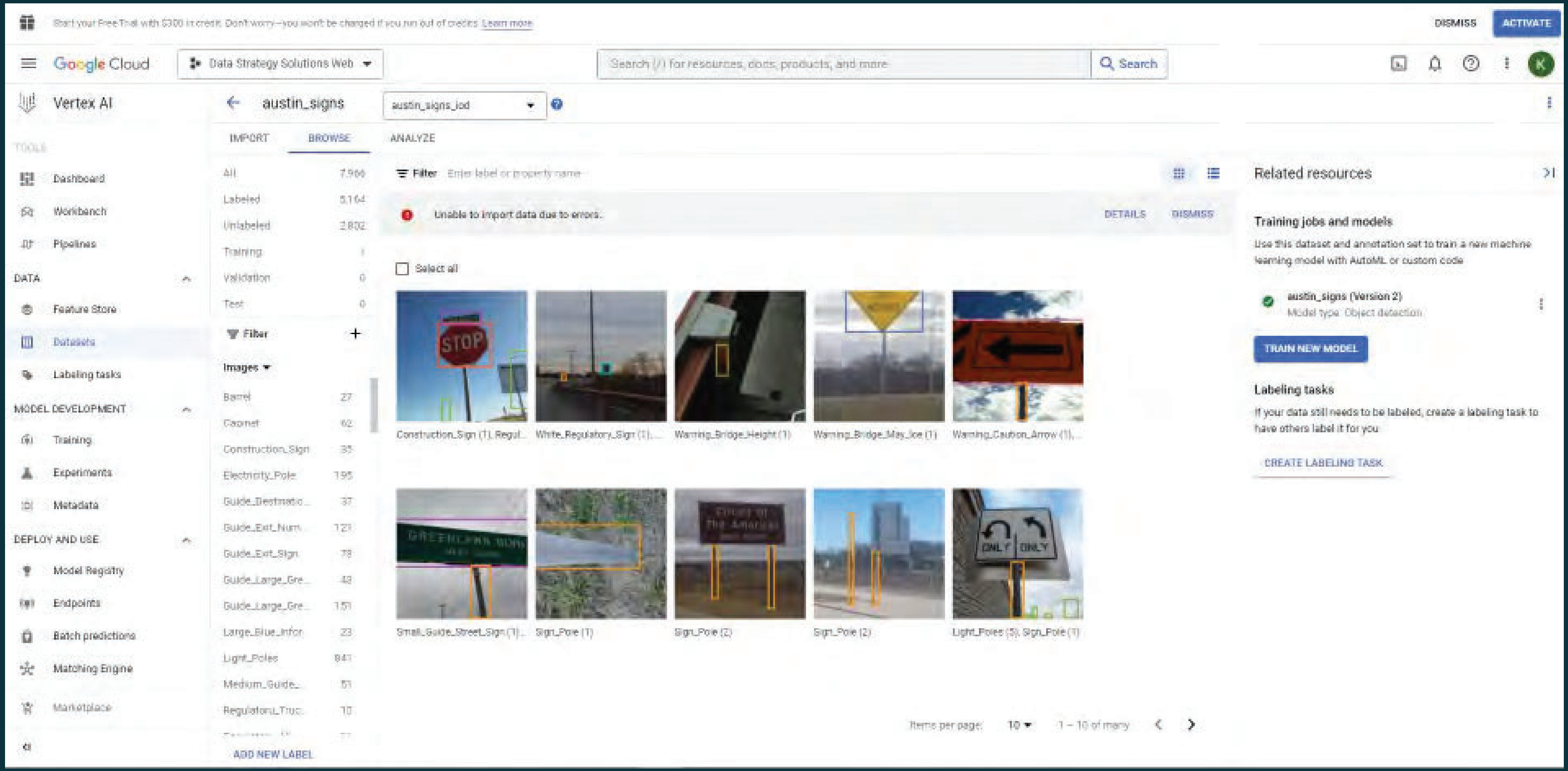
URL: https://cloud.google.com/vertex-ai/docs/start/introduction-unified-platform

Reasons to Choose GCP Vertex AI Pipeline Process

- The main objective is to optimize the video processing time and enable parallelization of the process
- GCP Vertex AI Pipeline Process will target to reduce end-to-end processing time approximately within the range of 30% to 70% for a single video file.
- The solution shall enable parallel processing of multiple requests, thereby increasing throughput using scalable architecture, enabling to get results faster consistently for multiple simultaneous video feeds.

Training Dataset Preparing – Labeling Process

- Label data using a tool such as Google Cloud's AutoML or a third-party labeling service.
- This involves manually annotating data to identify objects of interest and their locations on the map.



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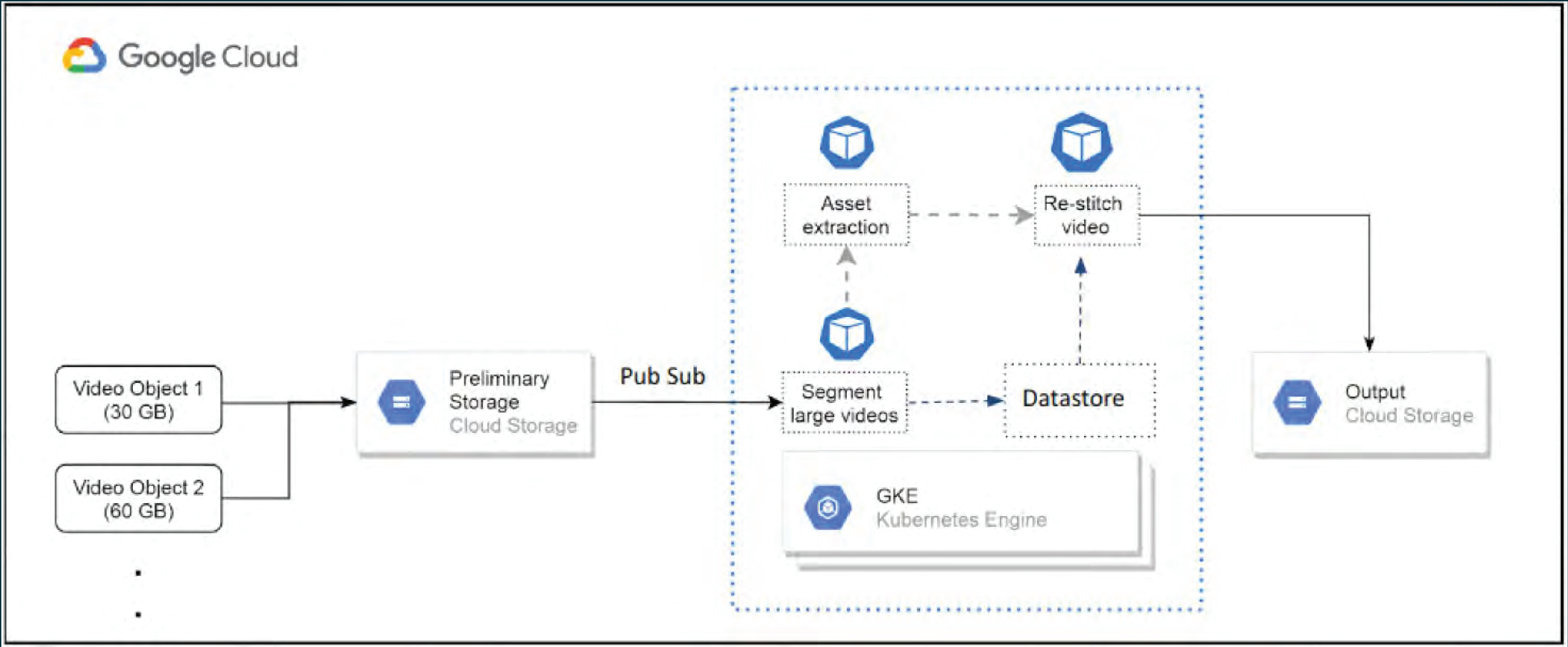
GCP Vertex AI Pipeline Process Architecture



Logic Sequence of the GCP Vertex ML Pipeline Process

1. Create a GCP account
2. Create a Google Cloud Storage bucket for data storage

Prepare Training Dataset -

3. Prepare Datasets - Prepare training data for labeling. Convert data to a compatible format and splitting into training and validation Datasets.
4. Label training data using a tool such as Google Cloud's AutoML or a third-party labeling service.
5. Import the labeled data into Vertex AI for model training.
6. Choose a model architecture and configure training parameters, such as the number of epochs and batch size.
7. Train the model on the labeled data using Vertex AI's distributed training infrastructure.
8. Evaluate the performance of the trained model using the validation set.
9. Deploy the trained model as a REST API endpoint for batch prediction.
10. Use GAIL or another Python library to preprocess data and make predictions on new, unlabeled data.
11. Feed the predictions into an MRF algorithm to determine the detected objects' location on a map.
12. Validate the results and refine the model as necessary

Model Evaluation

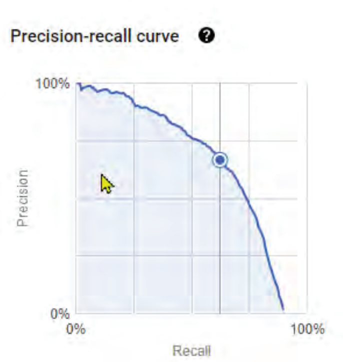
- Precision: It is defined as the ratio of the number of relevant variations or records of a particular class that have been classified to same class by the model to the total number of records in a dataset that have been classified to the same class by the model
  - Precision = Number of True Positive/(Number of True Positive + Number of False Positive)
- Recall: It is defined as the ratio of the number of relevant variations or records of a particular class that have been classified to the same class to the total number of records that belong to the category if the same class in the dataset
  - Recall = Number of True Positive/(Number of True Positive + Number of False Negative)

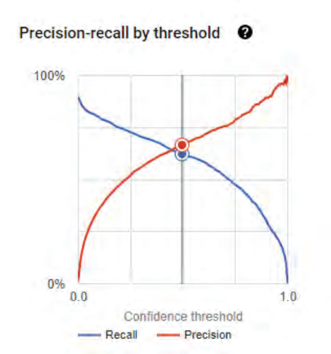
Initial Pipeline Running Result – Single Video

Over all Precision and Recall

All labels

Average precision	0.523
Precision	66.6%
Recall	62.3%
Created	Feb 11, 2023, 2:13:51 AM
Total images	5,164
Training images	4,087
Validation images	547
Test images	530





Yield

Regulatory_Yield

Average precision	0.802
Precision	82.4%
Recall	93.3%

To evaluate your model, set the confidence threshold to see how precision and recall are affected. The best confidence threshold depends on your use case. Read some example scenarios to learn how evaluation metrics can be used.

Stop Sign

Regulatory_Stop_Sign

Average precision	0.735
Precision	73.3%
Recall	84.6%

To evaluate your model, set the confidence threshold to see how precision and recall are affected. The best confidence threshold depends on your use case. Read some example scenarios to learn how evaluation metrics can be used.

No U-Turn

Regulatory_No_U_Turn

Average precision	0.824
Precision	100%
Recall	100%

To evaluate your model, set the confidence threshold to see how precision and recall are affected. The best confidence threshold depends on your use case. Read some example scenarios to learn how evaluation metrics can be used.

One-Way

Regulatory_One_Way

Average precision	0.766
Precision	62.1%
Recall	91.1%

To evaluate your model, set the confidence threshold to see how precision and recall are affected. The best confidence threshold depends on your use case. Read some example scenarios to learn how evaluation metrics can be used.

Wrong Way

Regulatory_Wrong_Way

Average precision	0.76
Precision	82.1%
Recall	88.5%

To evaluate your model, set the confidence threshold to see how precision and recall are affected. The best confidence threshold depends on your use case. Read some example scenarios to learn how evaluation metrics can be used.

No Left Turn

Regulatory_No_Left_Turn

Average precision	0.341
Precision	100%
Recall	25%

To evaluate your model, set the confidence threshold to see how precision and recall are affected. The best confidence threshold depends on your use case. Read some example scenarios to learn how evaluation metrics can be used.

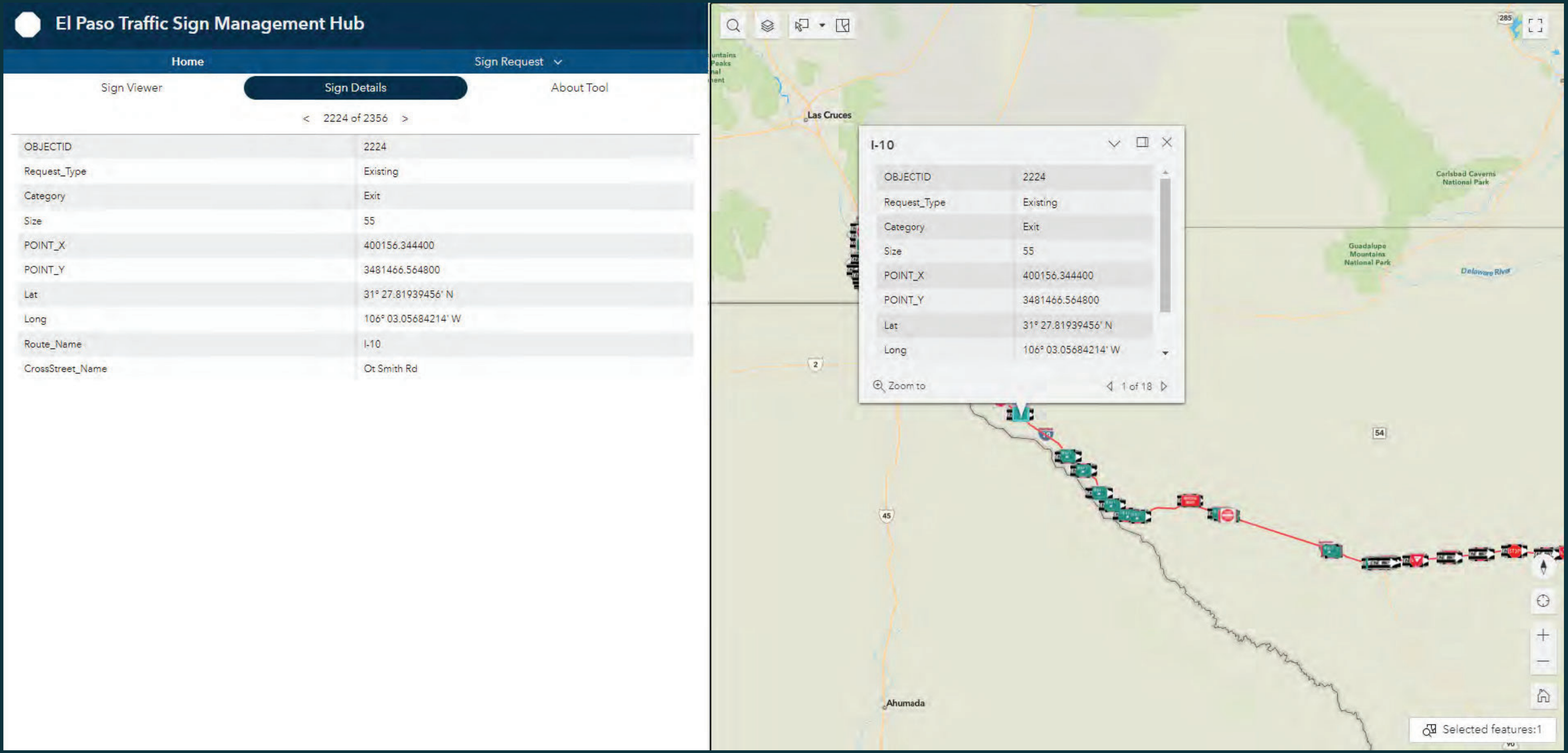
No Right Turn

Regulatory_No_Right_Turn

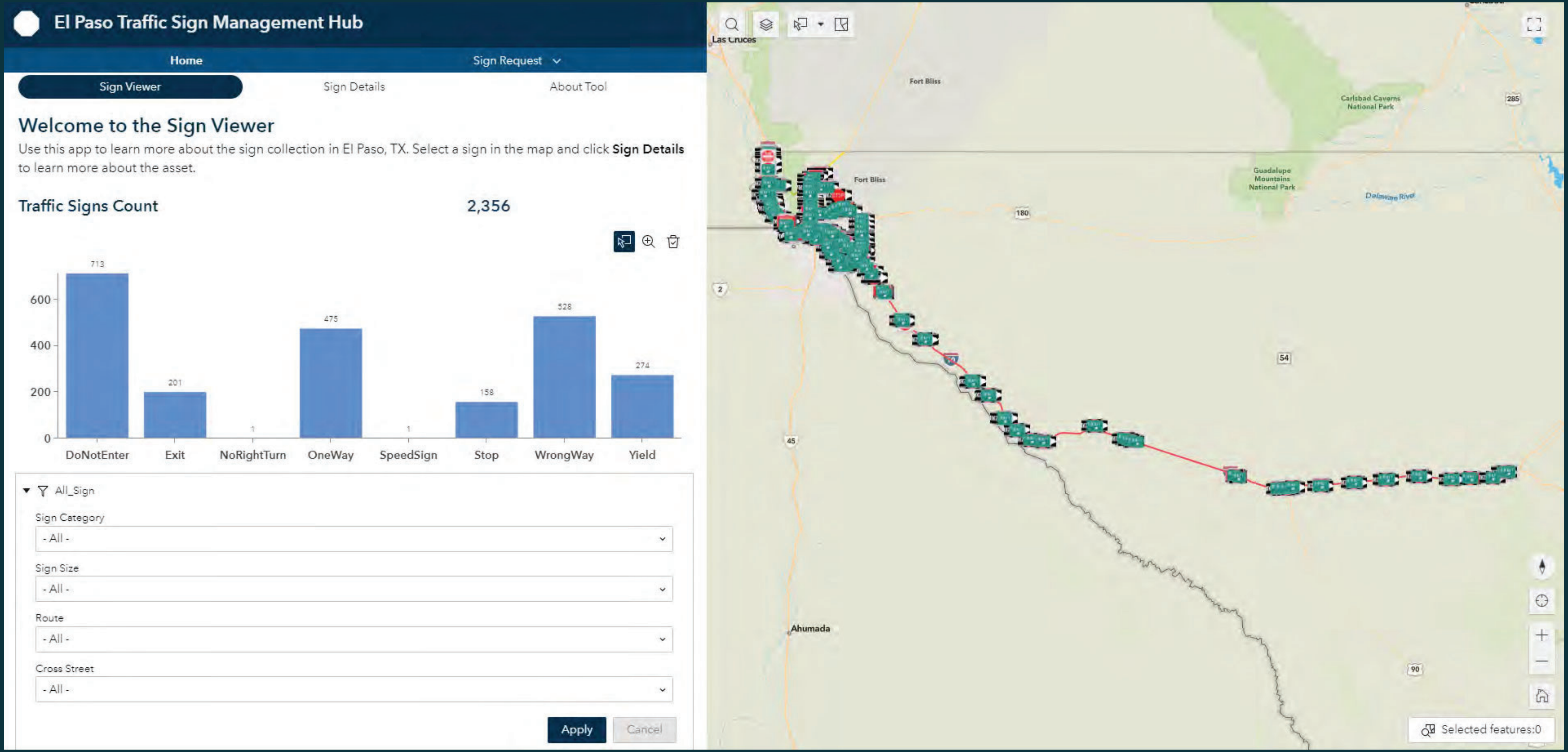
Average precision	0.176
Precision	100%
Recall	25%

To evaluate your model, set the confidence threshold to see how precision and recall are affected. The best confidence threshold depends on your use case. Read some example scenarios to learn how evaluation metrics can be used.

Results Presentation / Visualization Dashboard



Results Presentation / Visualization Dashboard



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Takeaways & Lessons Learn

- Lessons Learn in ML Dataset Preparing
  - Labeling Process is a Challenge
    - Having an organized and standardized processing procedure from the beginning is key.
    - Well-trained labelling team is also the key.
  - Label Sample Size Matters
    - As we can see from our model, when you are trying to achieve an overall high precision and recall you must ensure there is enough samples per label.
- Experiences of Using GCP Vertex AutoML Pipeline
  - The model and detection worked great, we can run our video through our pipeline and examine the frames for the signs.
  - The pipeline also uses the metadata to correctly position the detected signs.

Summary and Next Steps

- Taking advantage of cloud-based enterprise level ML tools such as GCP Vertex AI is a great way in helping the project data processing such as identifying and locating street signs, traffic equipment and safety equipment.
- The ML task requires a large dataset either custom or provided but will need some custom labels built in to serve the desired purposes.
- The GCP AutoML pipeline is an efficient pipeline when data is properly transformed and arranged accordingly.
- The next steps of the project will be focusing on fine tuning the model to gain a better overall performance

Thank You

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A Multi-task Learning Framework for Asset Inventorying and Condition Monitoring

Yaw Adu-Gyamfi
Assistant Professor
University of Missouri - Columbia

Presentation Goals

MULTIPLE TASKS

SINGLE MODEL

CAMERA ONLY

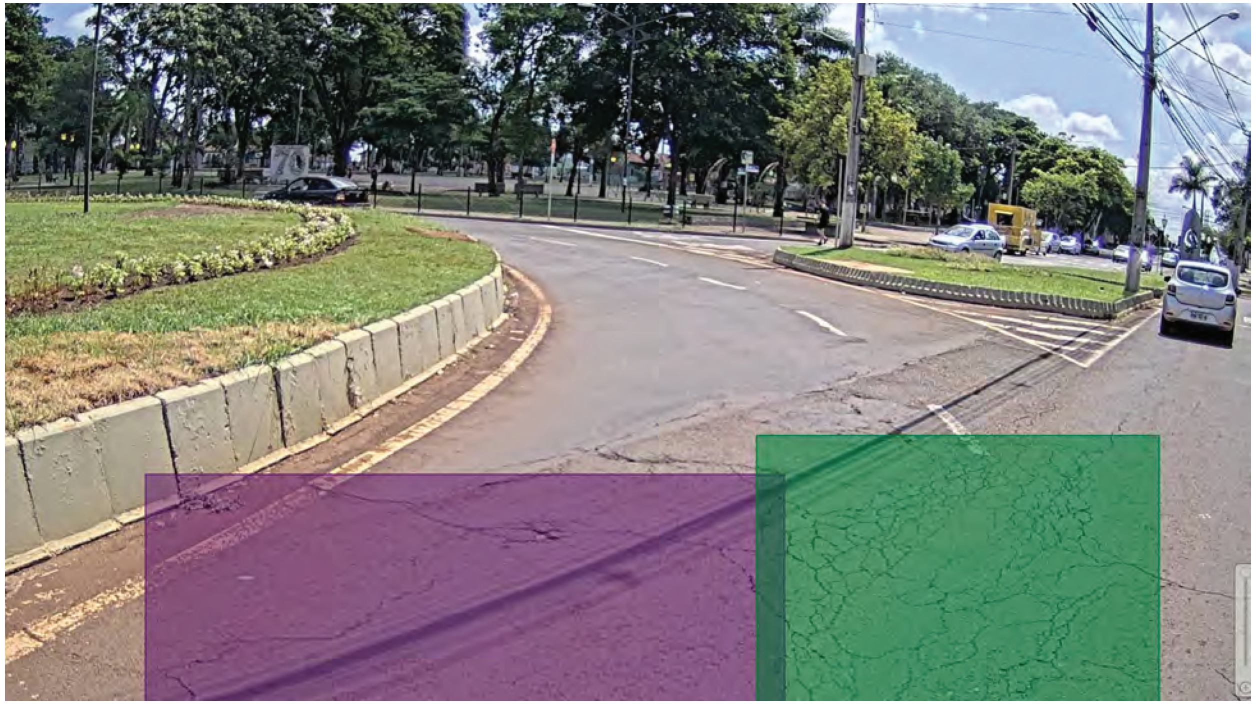
REALTIME

Presentation Goals

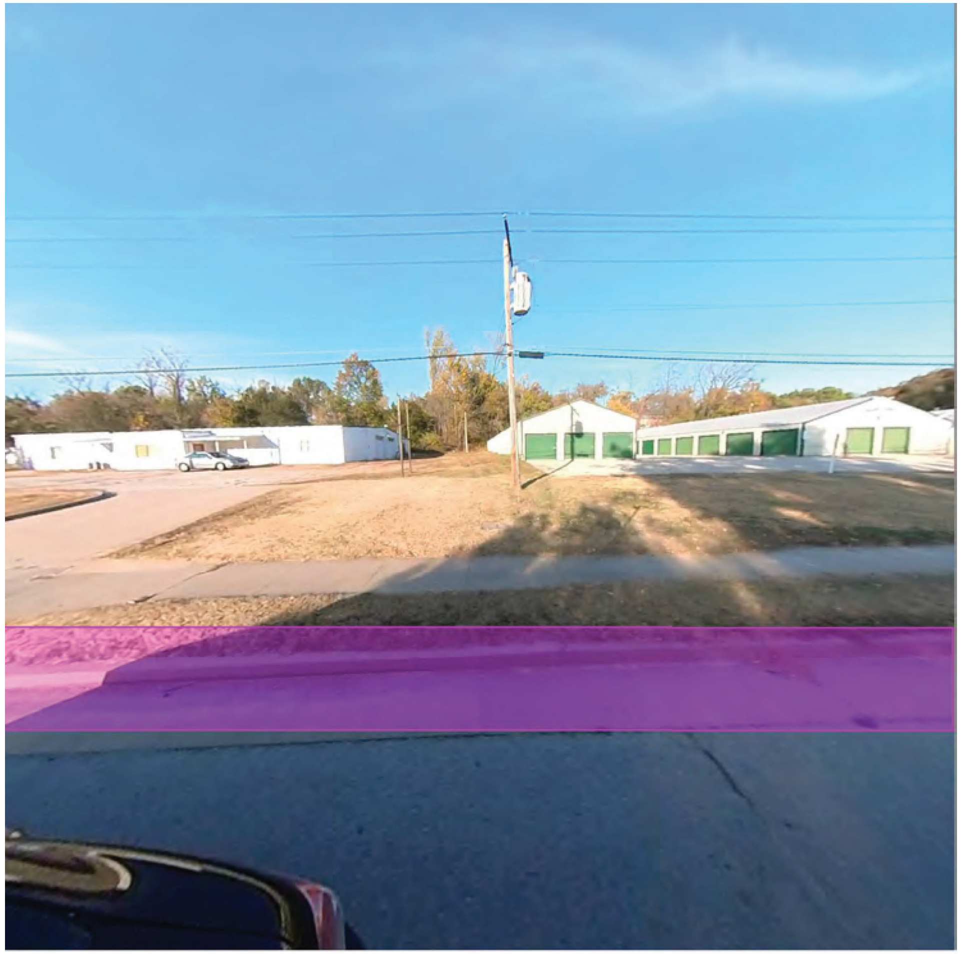
NIGHT

Presentation Goals

ASSETS – PAVEMENTS AND SIDEWALKS



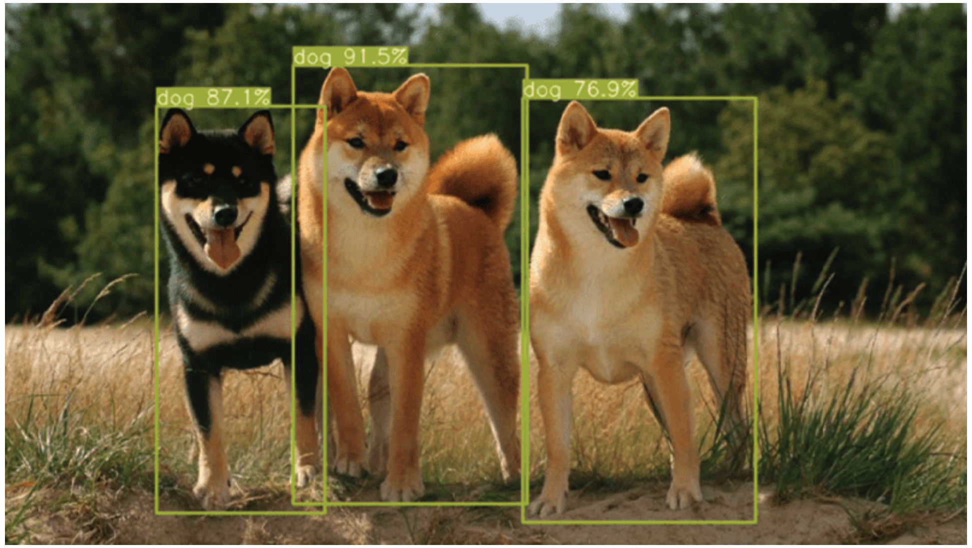
ASSETS – CURB & GUTTER

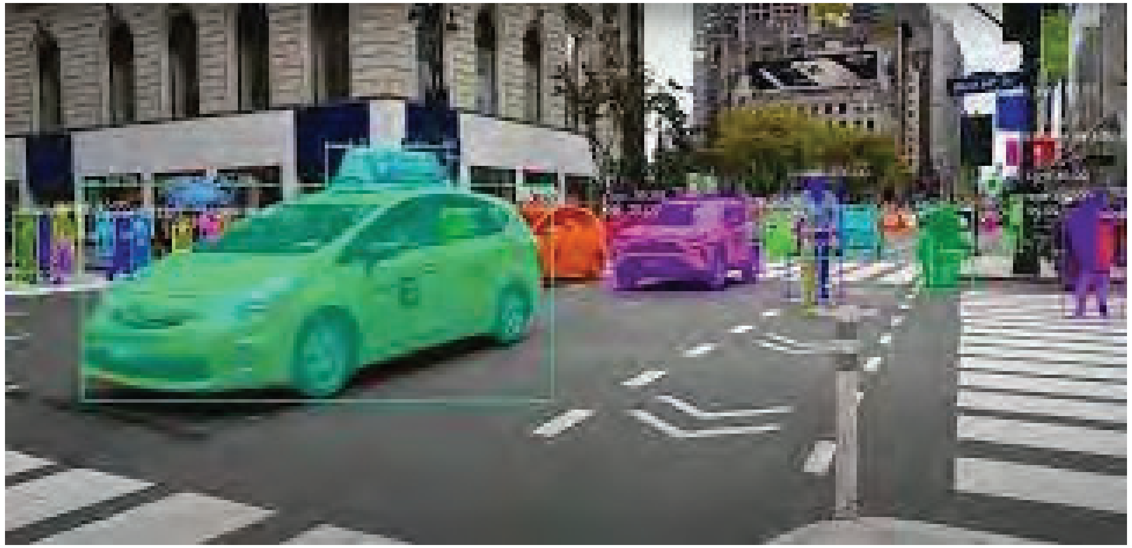


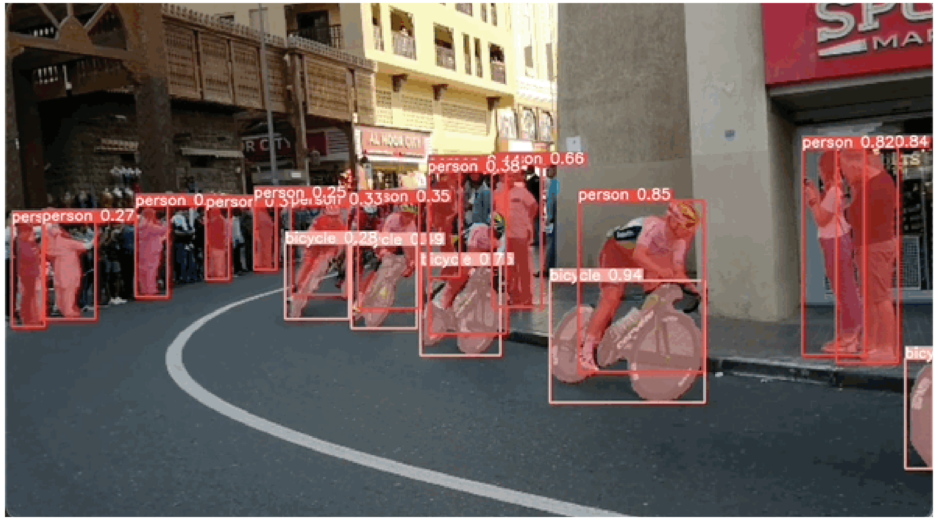
ASSETS – SIGNS & PAVEMENT MARKINGS

Sign Condition Evaluation - LiDAR

Existing AI Implementations







- Single Tasks

Tradition AI - Implementation Challenges

Why not multi-task

Computational Cost

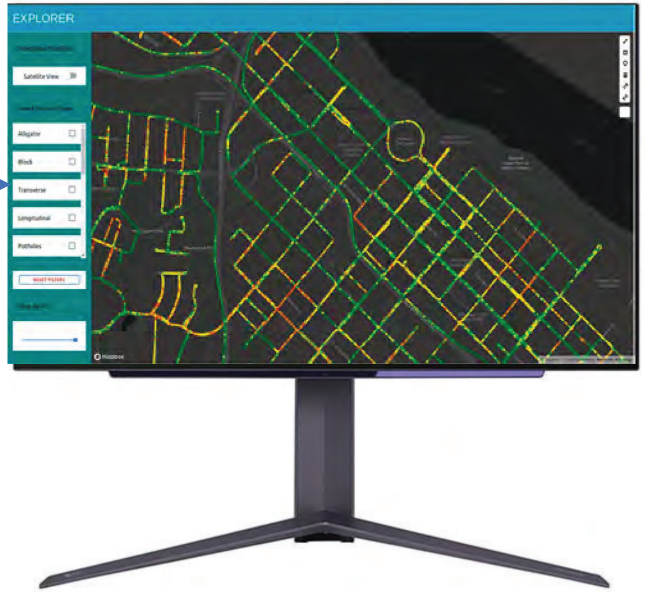
Accuracy

Proposed Implementation

Detect

Segment

Condition



Hardware Components

GoPro 11 Black

Jetson Orin

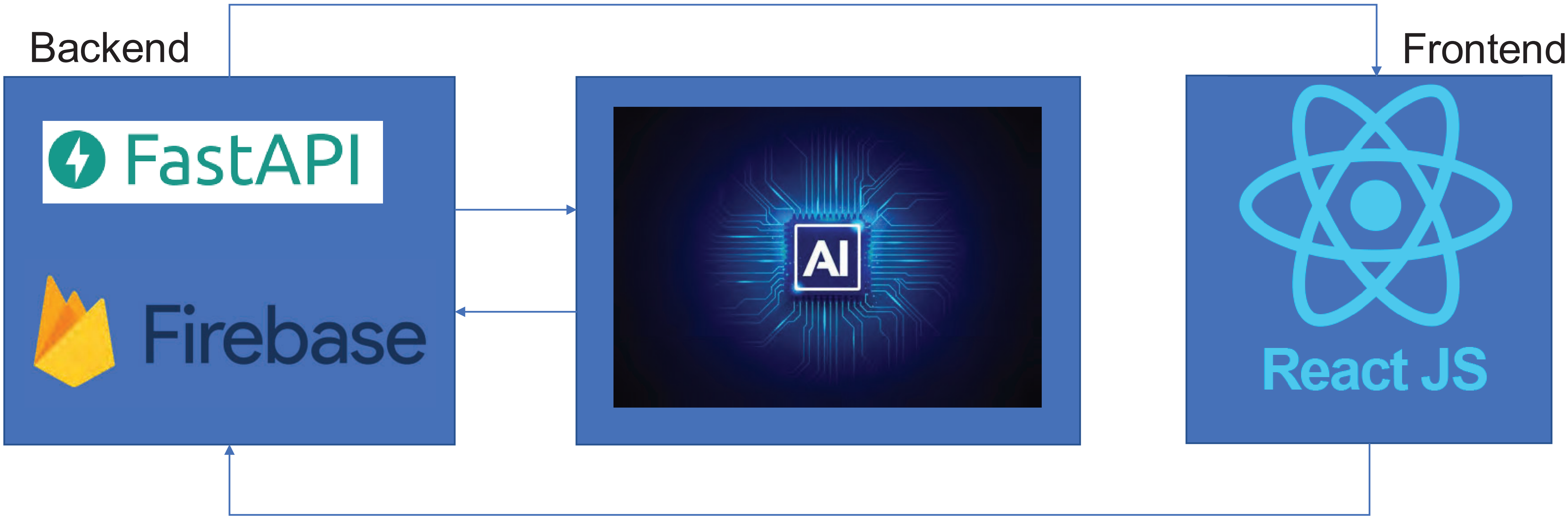
Ouster LiDAR – OS-2 -128

Mounts

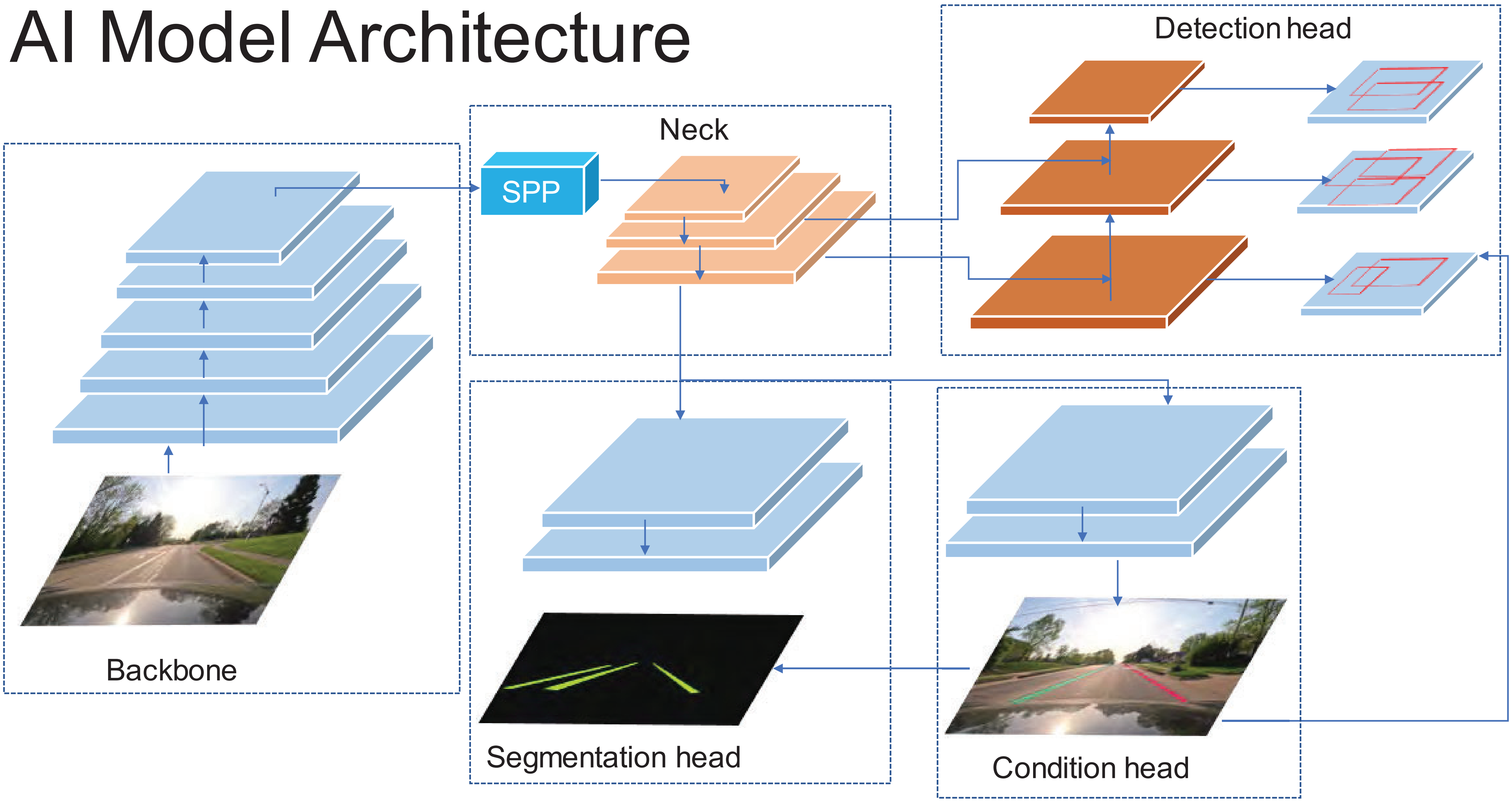
Monitor

Battery

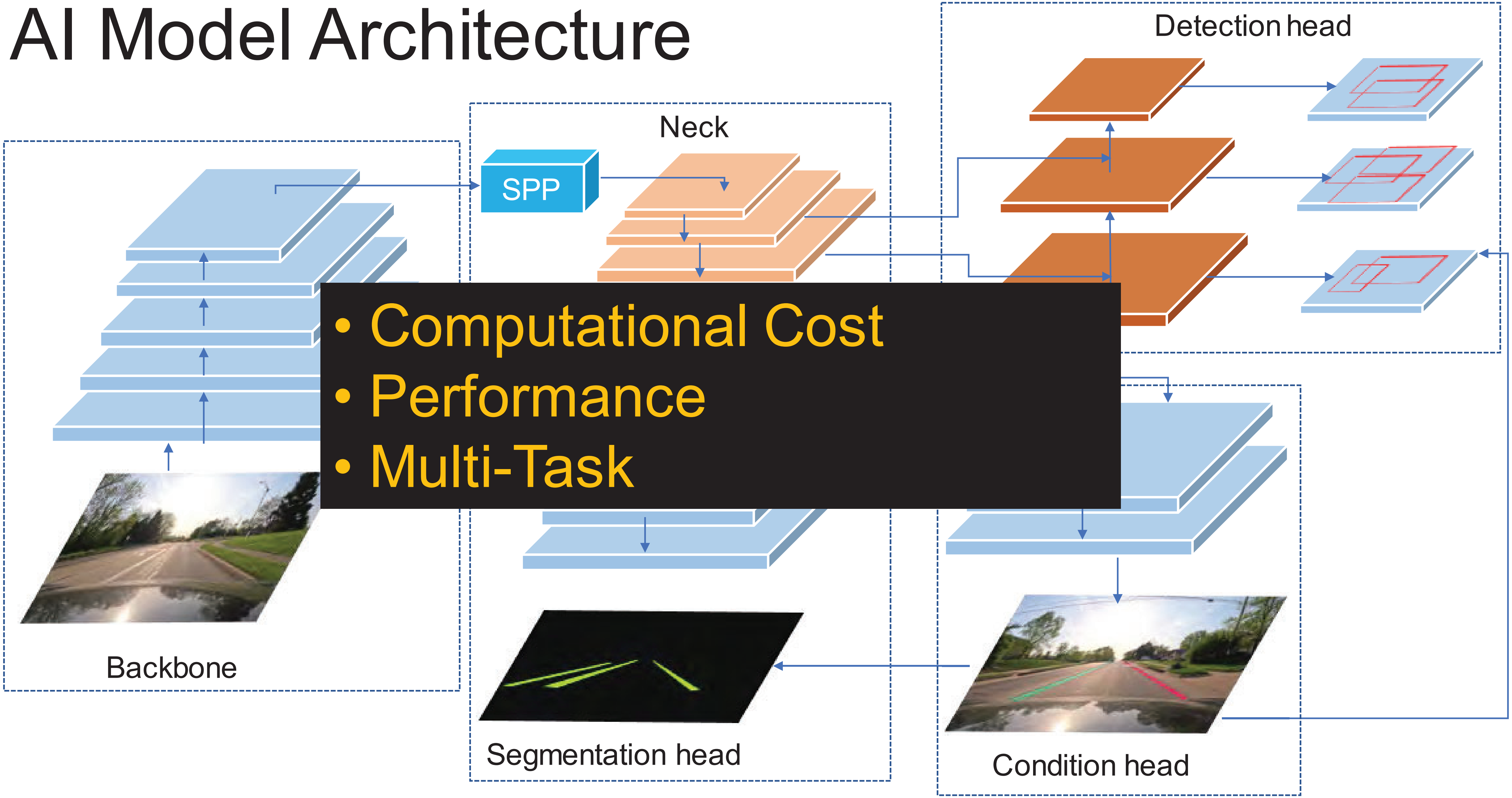
Software Components



AI Model Architecture



AI Model Architecture



- Computational Cost
- Performance
- Multi-Task

Training Data Generation

- Data Alignment
- Sign condition – good, fair, poor

Training Data Generation

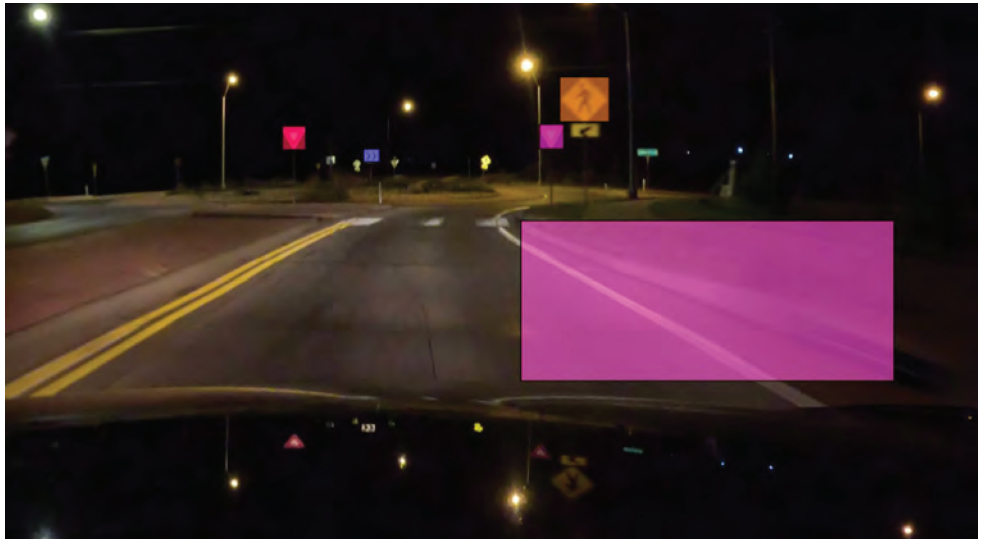
- Data Alignment
- Sign condition – good, fair, poor

Training Data Generation

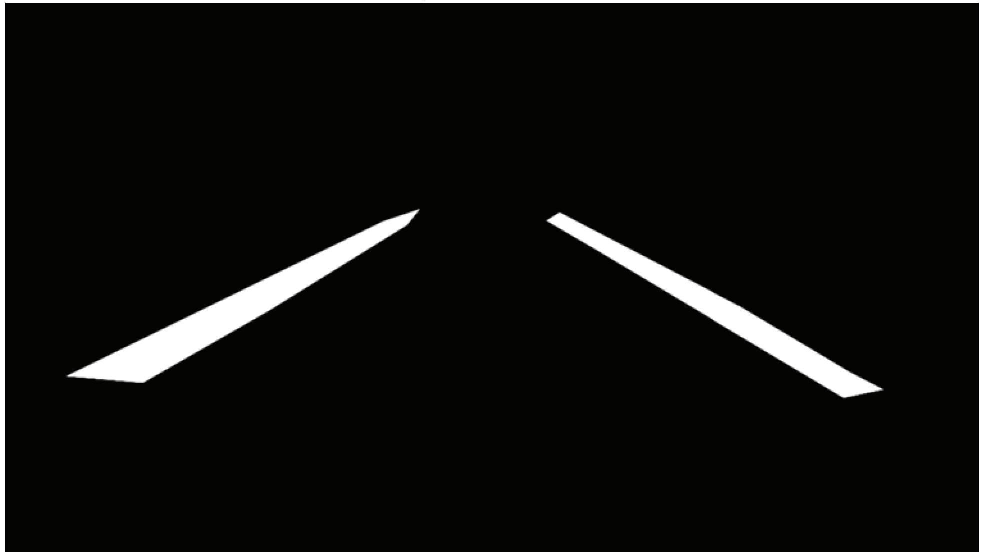
- Data Alignment
- Sign condition – good, fair, poor

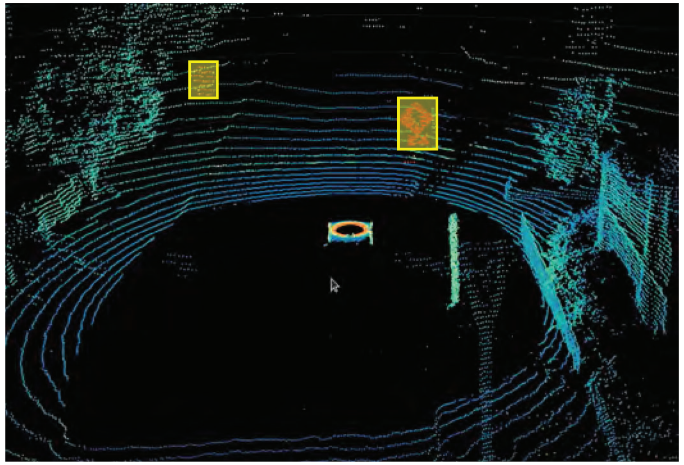
Training Data Generation

Bounding Boxes



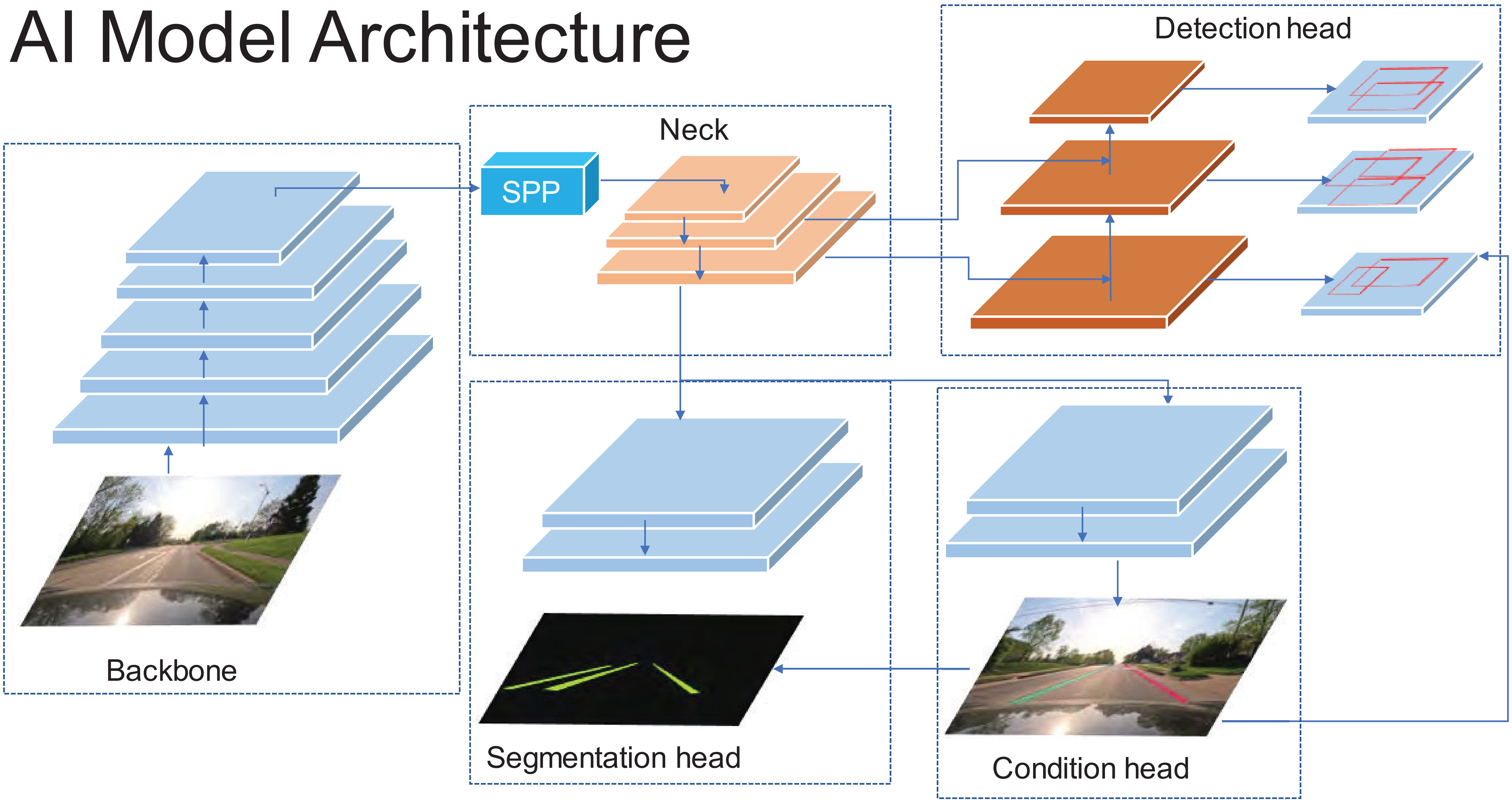
Segmentation





LiDAR Reflectivity

AI Model Architecture



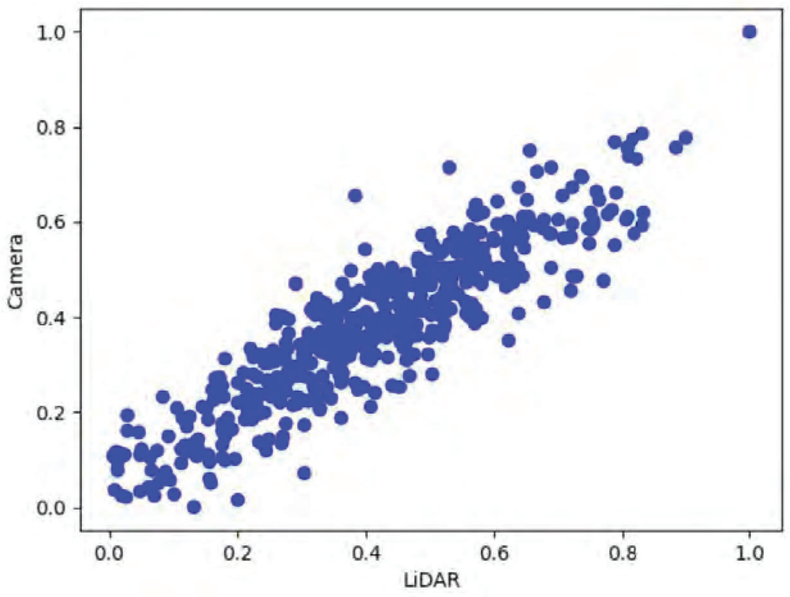
Model Evaluation – Detection & Segment

Model Evaluation – Detection & Segment

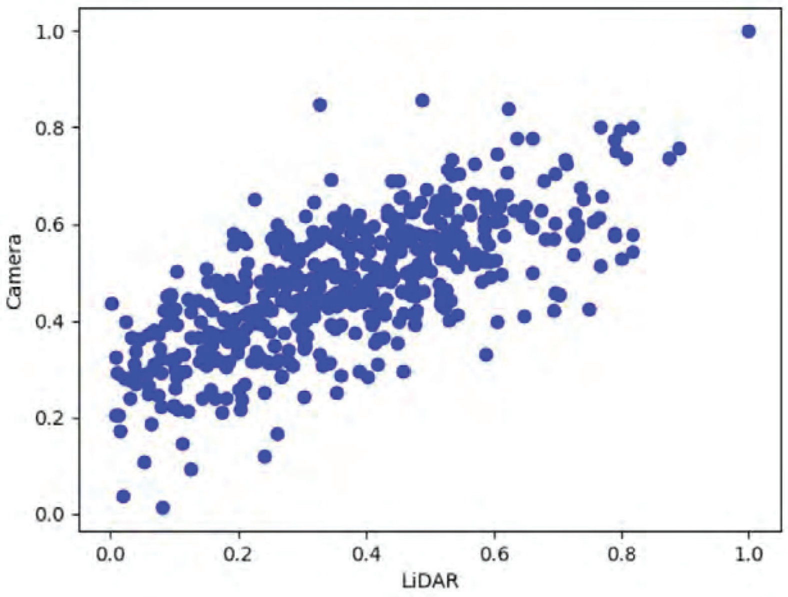
	Recall (%)	Precision (%)	mIOU (%)	Accuracy (%)	Speed (fps)
Pavement Distress	87.0	76.5		73.8	
Pavement Marking			73.7		
Traffic Signs	96.5	93.5		94.0	41
Cars	92.7	88.5		87.5	
Side-Walk Distress	76.5	72.8		67.8	

Model Evaluation – Condition

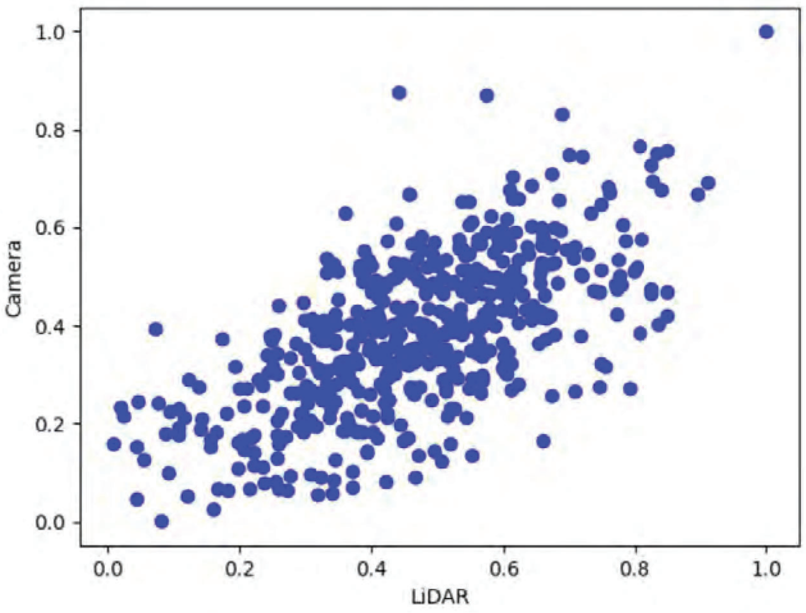
10 FEET



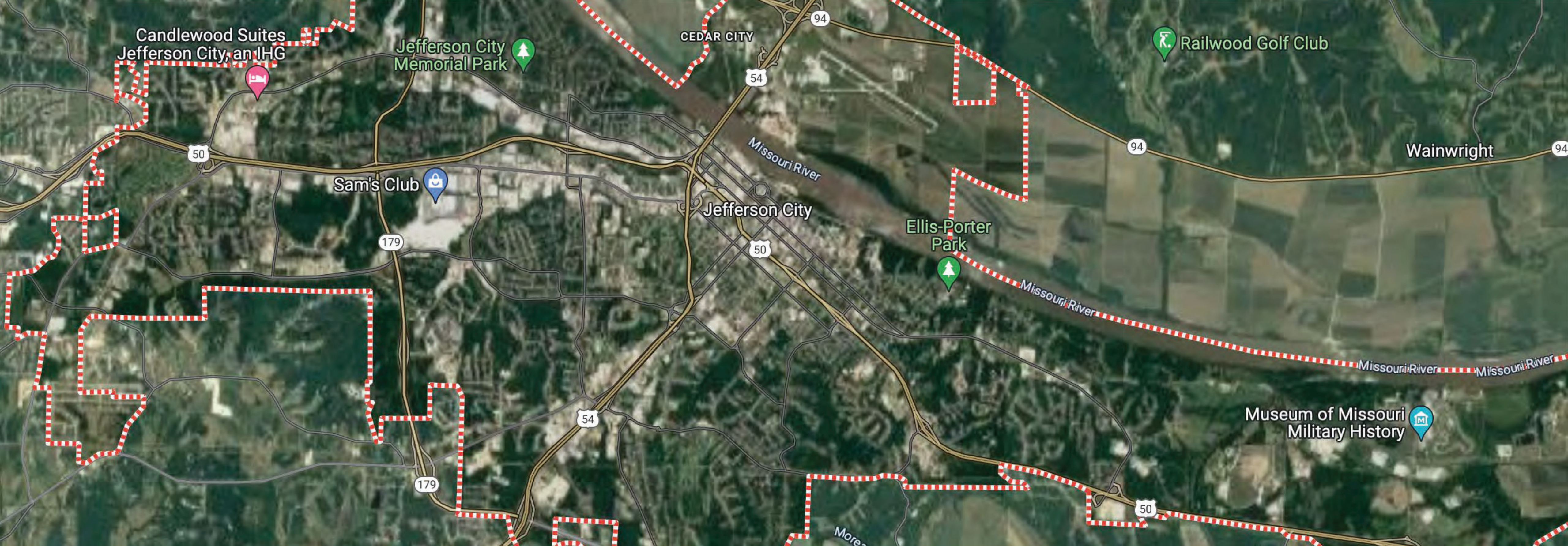
20 FEET



30 FEET



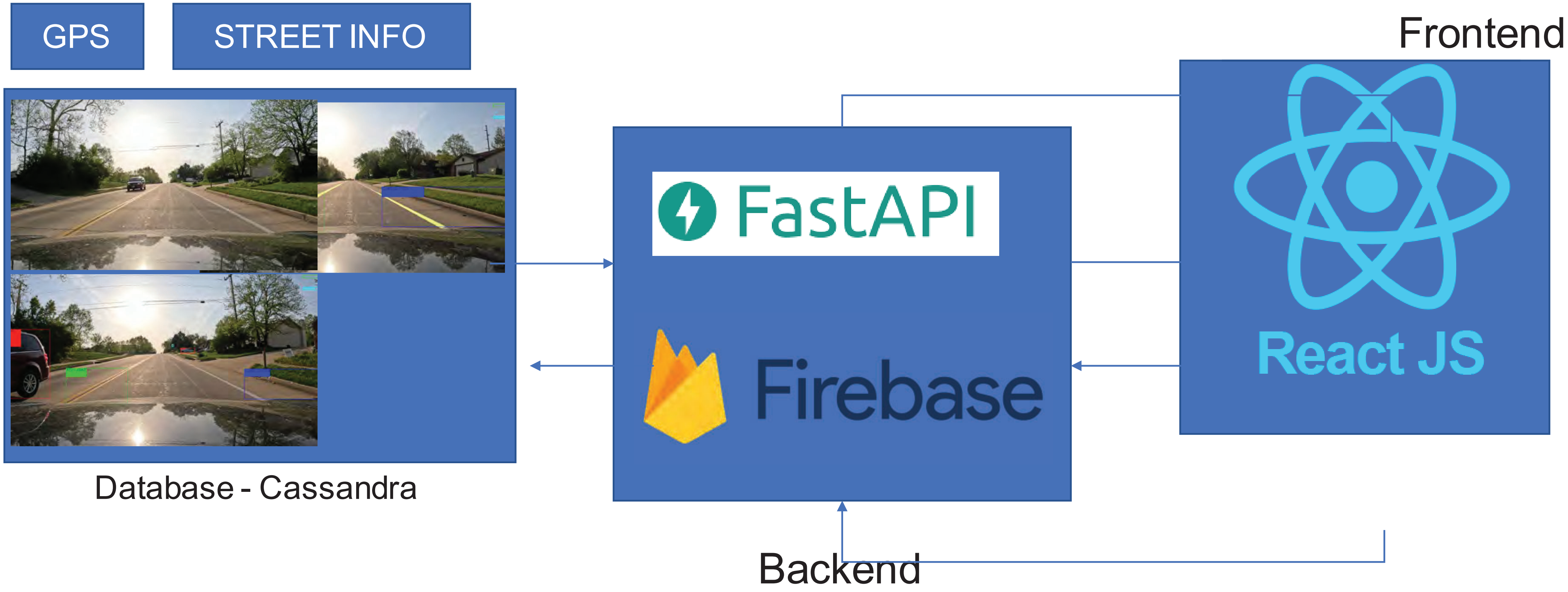
Model Evaluation – Condition



Test Run

- Jefferson City
- 250 miles of roadway
- Survey completed in 3 days.
  - 2 GoPro Cameras.
  - Jetson Orin.
  - Realtime.

Web Integration



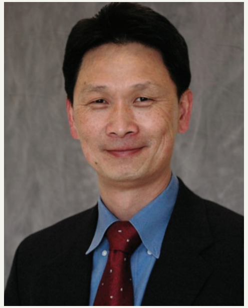
Web Integration

Lessons Learned

- Hardware
- Model
- Visualization

Thank You

Today's presenters



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Bo Wang
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Upcoming events for you

May 22

TRB Webinar: Equity in Artificial Intelligence Applications

July 8

TRB's National Conference on Transportation Asset Management

https://www.nationalacademies.org/trb/events

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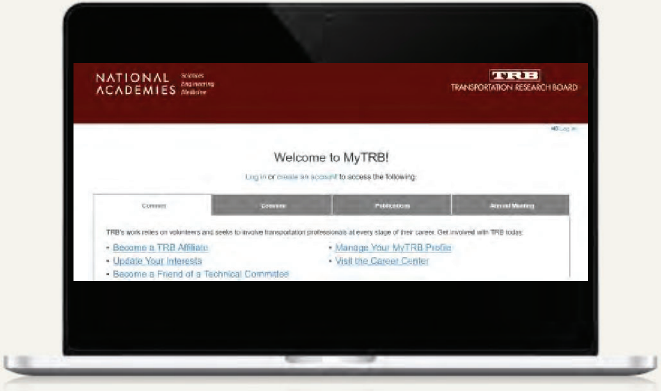
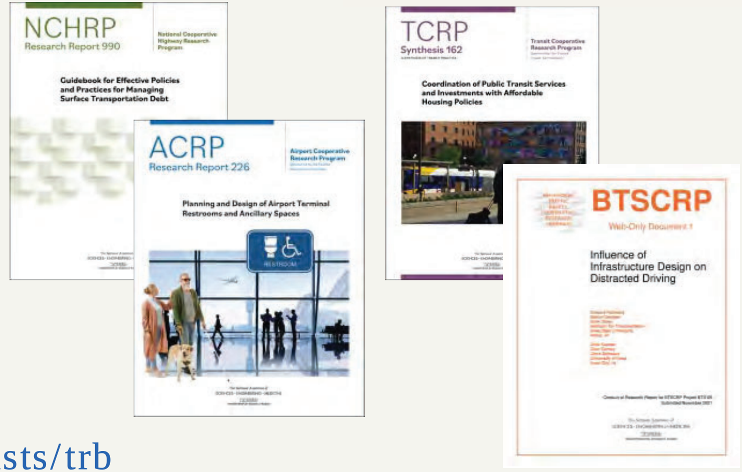


- Become a Friend of a Standing Technical Committee
  - Network and pursue a path to Standing Committee membership

- Work with a CRP



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