New Directions in Safety R&D: AI, Big Data Analytics & Computer Vision Applications

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Keywords

- (Pro) Active Traffic Management (PTM)
- Big Data
- Real-Time Applications
- Computer Vision and Machine Learning Applications
- Visualization

Safety Prediction

Provide Predictive Insights for Road Safety

New Data

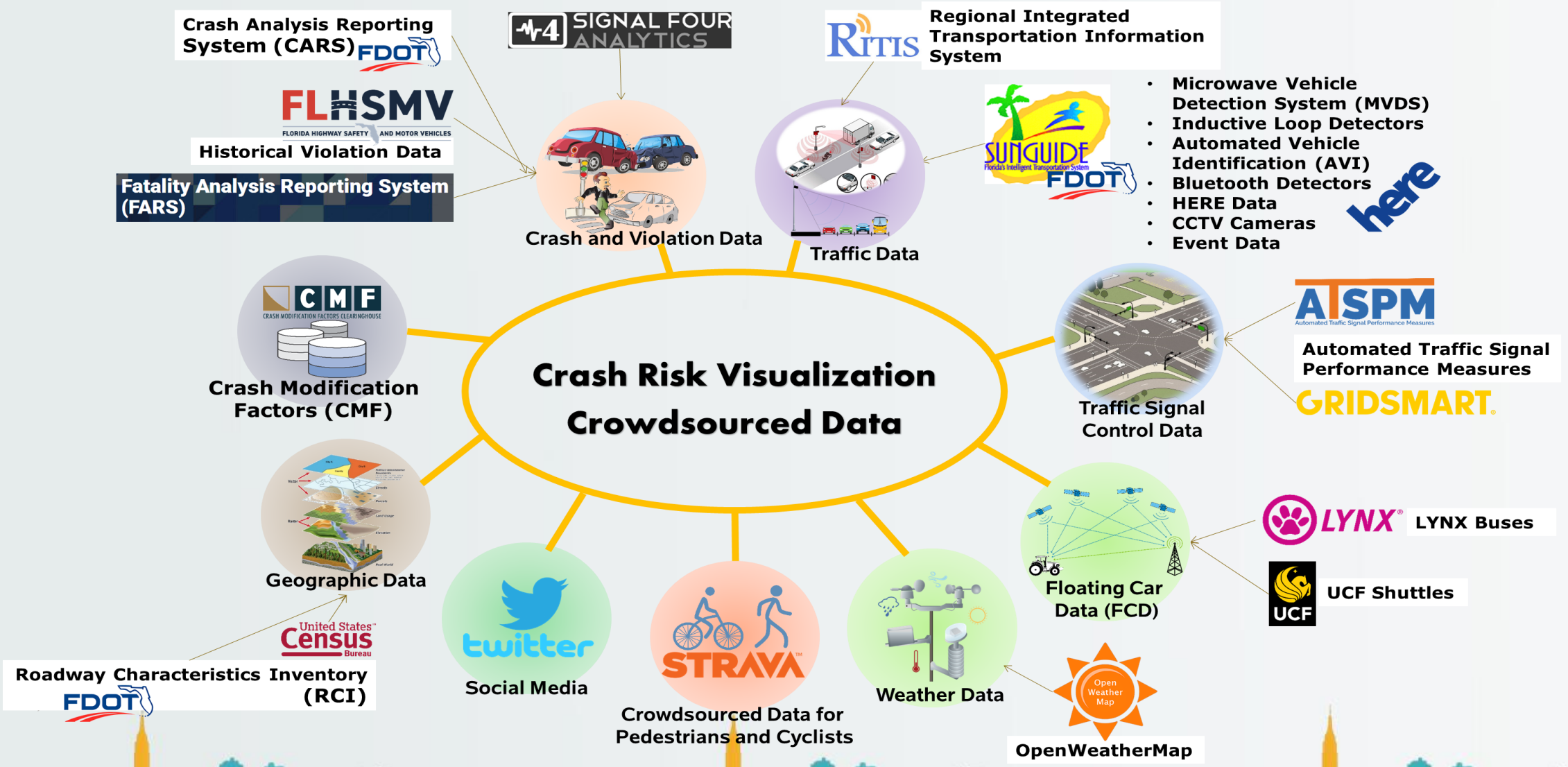
Using AI Techniques for Data Collection

Safety Applications

Improvement by Deploying State-of-the-art Technologies

Big Data

DATA-INFORMED TOOLS

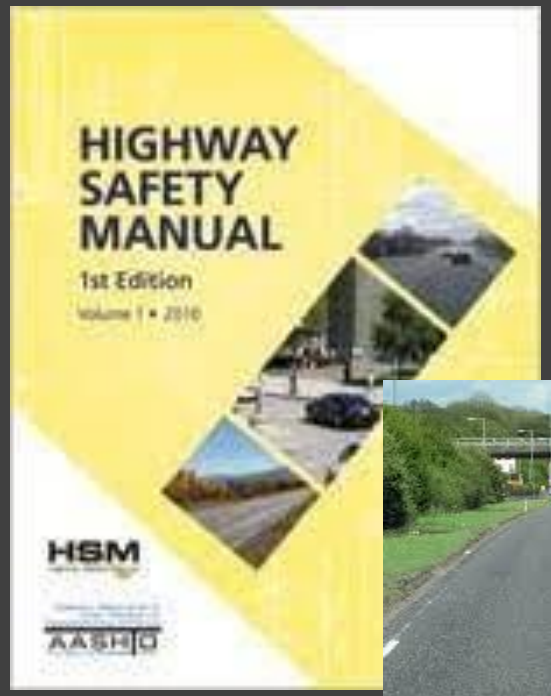


Safety Analysis Data

Traditional Methods

Data

Highly Aggregate Data/ Static Data



State-the-art Methods (AI)

Data

High-resolution
Big Data
Real-time
New Data Type

High-resolution Big data in real-time

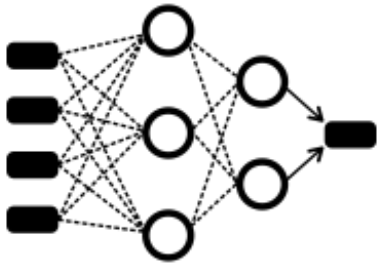
Infrastructure Data
Probe Vehicle Data
ITS Data
Signal Timing
Weather
CAV
Etc.

New Type of Data Sources

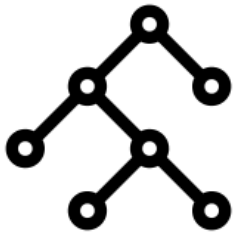
Image
Video
Smartphone
crash Narrative
IoT
Etc.

AI applications in traffic safety

Prediction



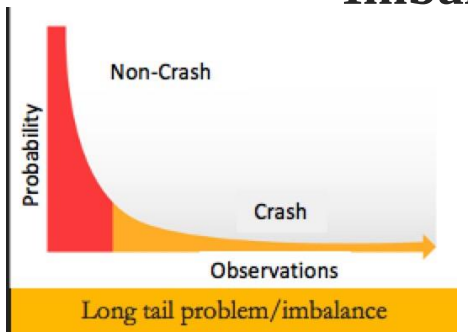
Neuron-based model
(e.g., CNN, LSTM)



Tree-based model
(e.g., XGBOOST)

- *Investigate nonlinear relationship between variables*
- *Handle large data*
- *Handle new data sources (high-dimension, time-series)*

Imbalance data issue



Generate Artificial Data

- Generative Adversarial Networks (GAN)
- Variational Autoencoder (VAE)

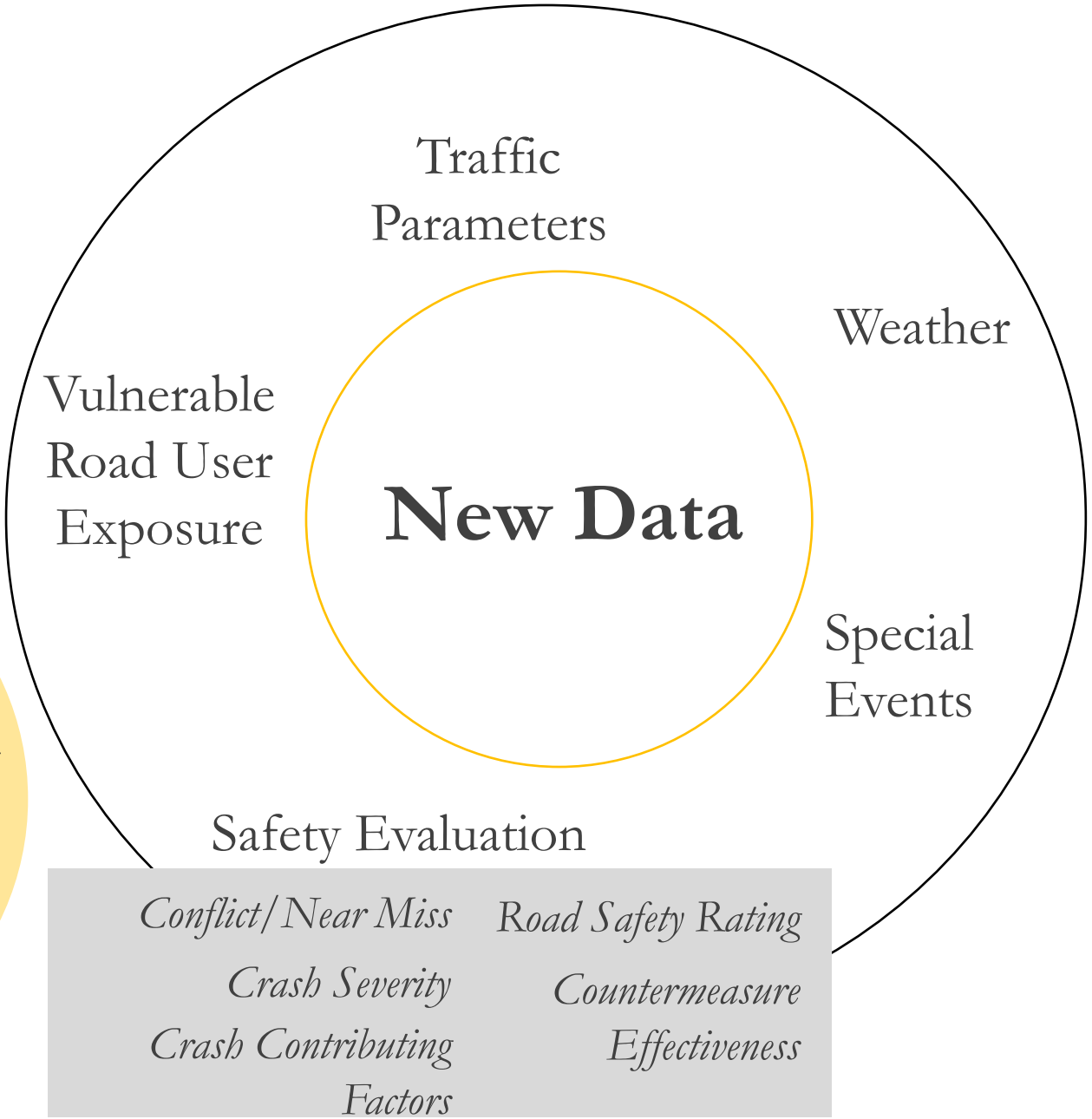
AI-based Data Collection

Data Source

- **Emerging sensors**: Camera, LIDAR, Sonar, Radar, UWB;
- **National wide/worldwide data**: Telematics data, CCTVs, Google Street View, Satellite Images, Crash Report

Advantage

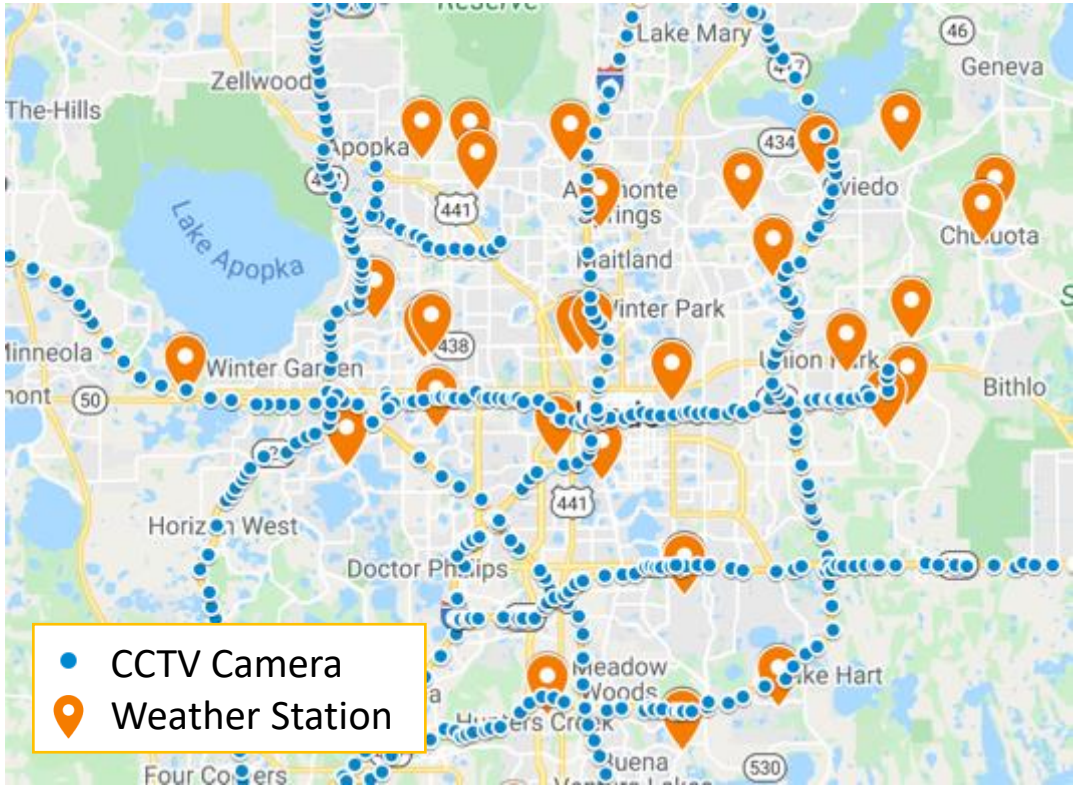
- Generate new type of data
- Reduce the cost/improve the efficiency for data collection
- Wide Coverage

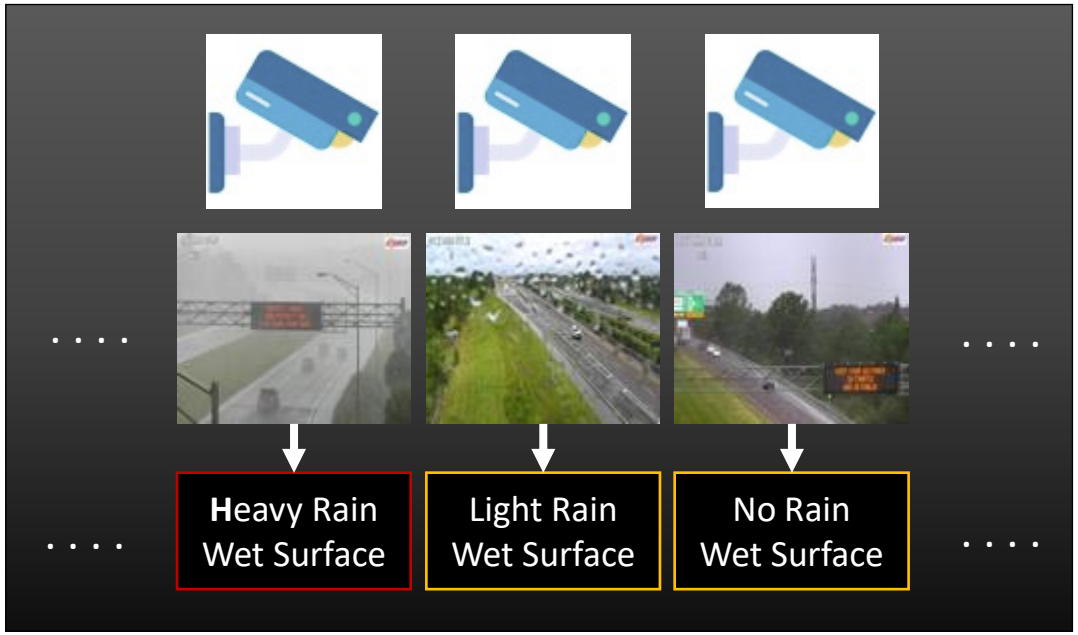


AI-based Data Collection

Camera-Based Rain and Road Condition Detection

- Ground weather stations provide accurate measurement of rain but are:
  - sparsely distributed in comparison to traffic cameras
  - not necessarily positioned near roads
  - cannot assess road condition
- CCTV cameras are spaced 0.5mi-1.0mi apart
- Using state-of-the-art computer vision algorithms to detect:
  - 3-level rain condition [heavy rain, light rain, no rain]
  - road surface condition [wet, dry]
- Obtaining real-time, high-frequency, granular observation of rain and road surface condition





Smart Corridor

Sound

Camera

Lidar

UWB

WIFI

Detection

Prediction

Prevention

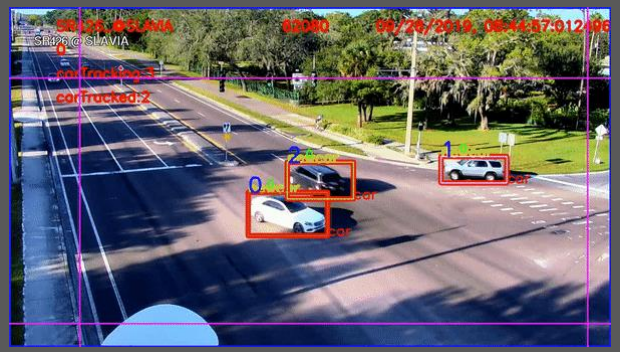
Decision

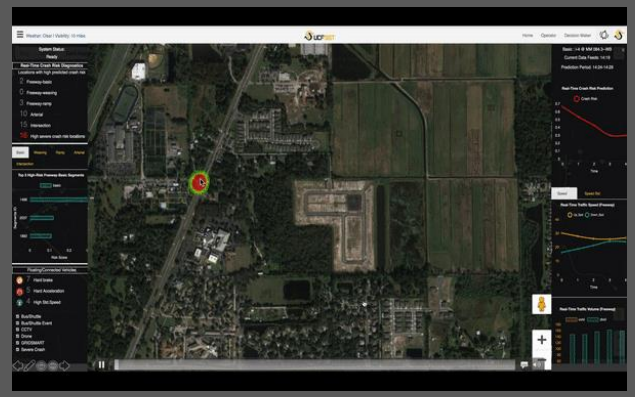
Evaluation

Real-time

Safe

smooth





- UCF SST Data Visualization Platform

Precise

Connected

Adaptive

Management platform

- Signal timing
- Count
- Event
- Speed
- Visualization

Warning system

- I2P
- I2V

Sharing

- Data
- Warning
- Event
- Signal phase and timing (Spat)
- Map data message(MAP)
- Basic safety message(BSM)
- Cooperative awareness message(CAM)
- Collective perception Message(CPM)

AI-based Data Collection

Detect and predict vehicles' maneuvers

Smart Phone

Global Positioning System (GPS)

Cellular positioning

Accelerometers

Magnetometers

Gyroscopes

Modeling

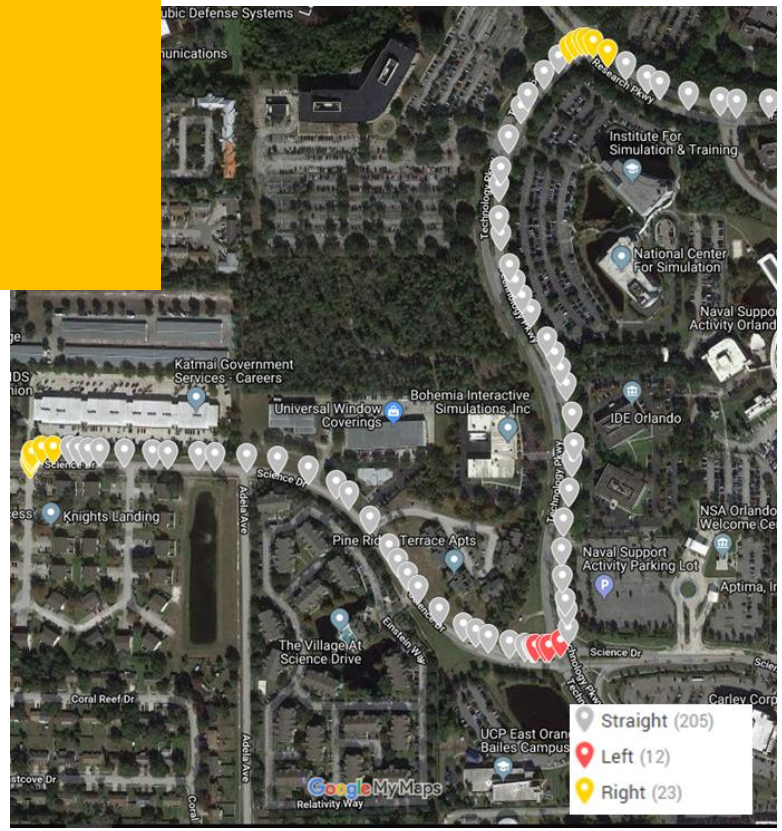
Gradient Boosting

Random Forest

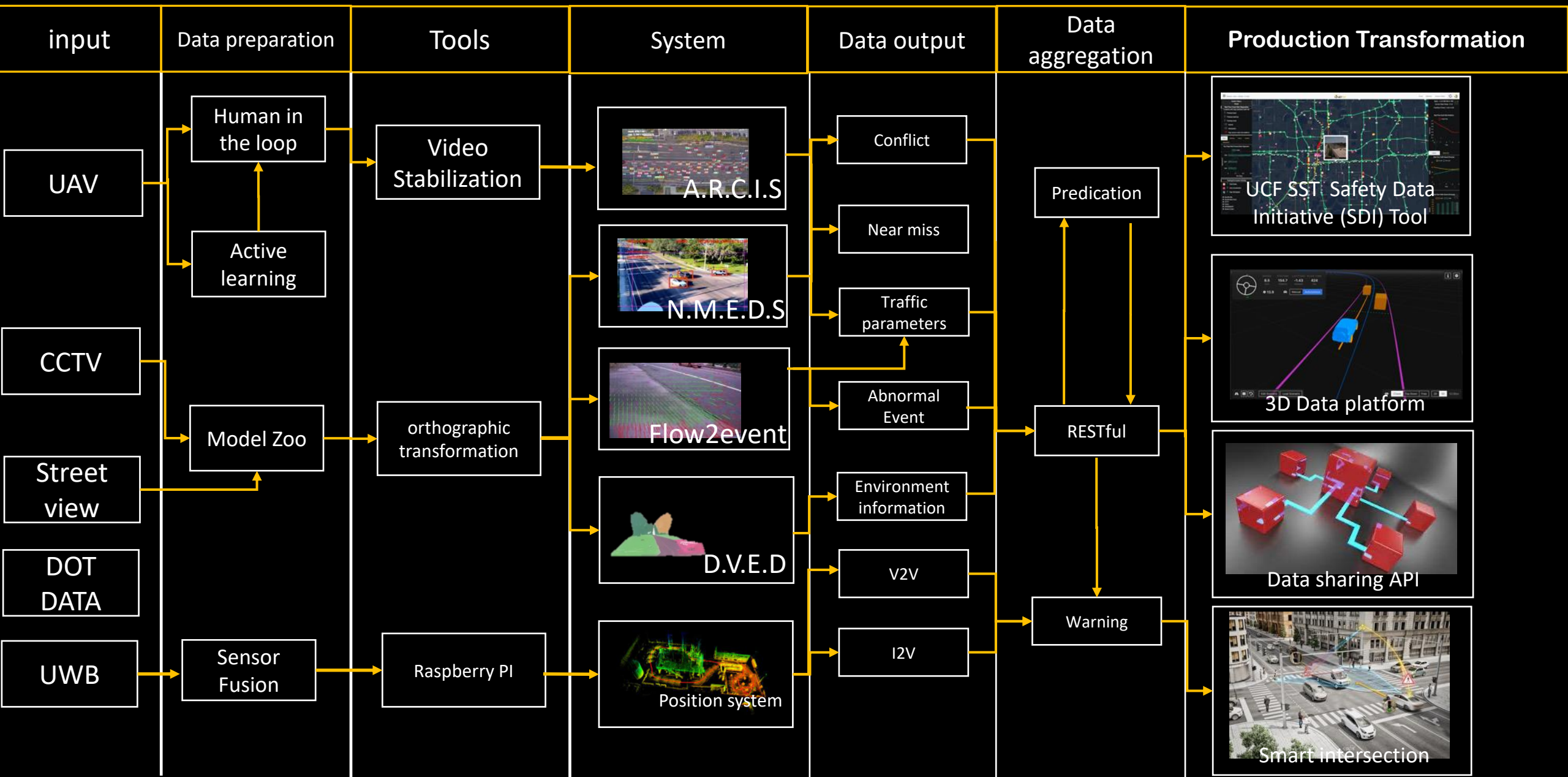
KNN

SVM

- Identify vehicles' movements including left turn; right turn; through; and U turn;
- Random forest method provides the best identification result and could classify vehicles' movement with high accuracy;



UCF SST System Overview

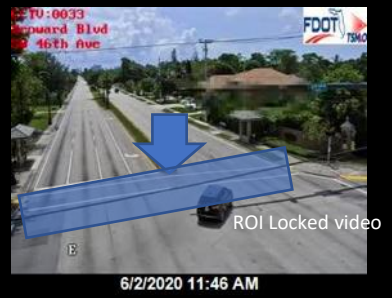


Data Processing

Data Pipeline

Camera Calibration

Land-Mark



Input video

Optical flow

Detection

One stage

- YOLO
- SSD

Two stage

- MaskRCNN
- Fast-RCNN
- Faster-RCNN

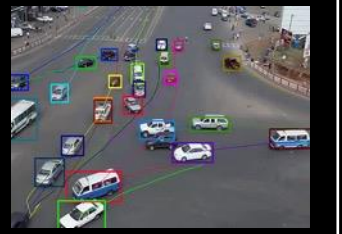
3D pose detection

- openPose
- PIFPAF
- COCO-Pose

Tracking

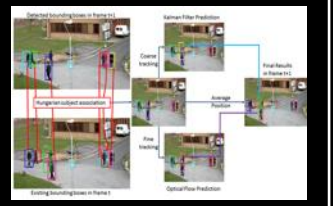
Short term tracking(frame t+1)

- CSRT
- Center-Track



long term tracking(frame t+n)

- RE-ID
  - Trajectory prediction



Traffic Data

- Volume, Speed & Headway estimation, vehicle classification
  - Real-time volume, speed estimation
  - Vehicle classification (passenger car, motorcycle, bus, truck)
  - Historical trajectories extraction
- Vulnerable road user count & speed estimation
  - Pedestrian & cyclist
  - Intersections
  - Arterials
- **Behaviors & Human factors**
  - Crossing behavior
  - Turning behavior
  - Cyclist gesture
  - Age
  - Gender
  - Pedestrian step analysis
- Conflict diagnostics based on conflicts of all road users including drivers, pedestrian, cyclists
- Abnormal events identification and management (e.g., adverse weather, hurricane)
- Countermeasure effectiveness estimation/before-after analysis
- Violation/Events identification (e.g. crash, queue)
  - *-support first responder*

Automated Roadway Conflicts Identification System (A.R.C.I.S)

UCF SST computer vision platform

About ARCIS

This system, applicable in particular to road traffic analysis, uses drone/Unmanned Aerial Vehicle (UAV) videos. The systems can generate the following types of outputs using drone/UAV video data:

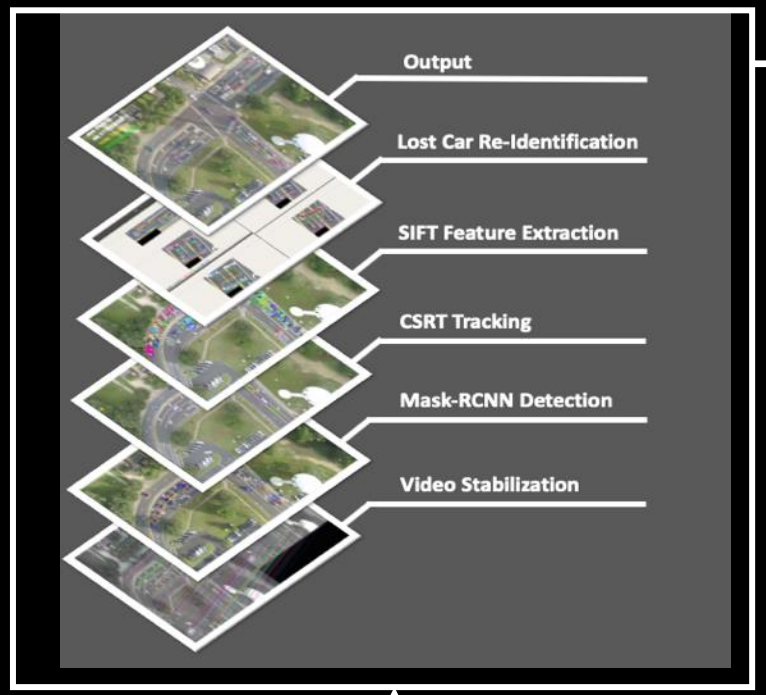
- Trajectory data of road users including vehicles and vulnerable road users
- Road users' classifications
- Traffic statistics (e.g., volume, speed)
- Safety indicators (e.g., Post-Encroachment Time (PET))

- DJI Phantom 4
  - 1920 ×1080 resolution
  - 30 FPS
  - 120 feet
  - 23 minutes

Automated Roadway Conflicts Identification System (A.R.C.I.S)

Automated Roadway Conflicts Identification System (A.R.C.I.S)

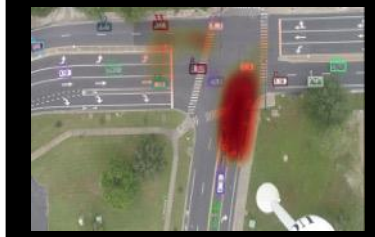
Pixel to pixel manner automated safety diagnostics and conflict identification system



Drone
Video Feed

- Vehicle Length and Width
- vehicle trajectories

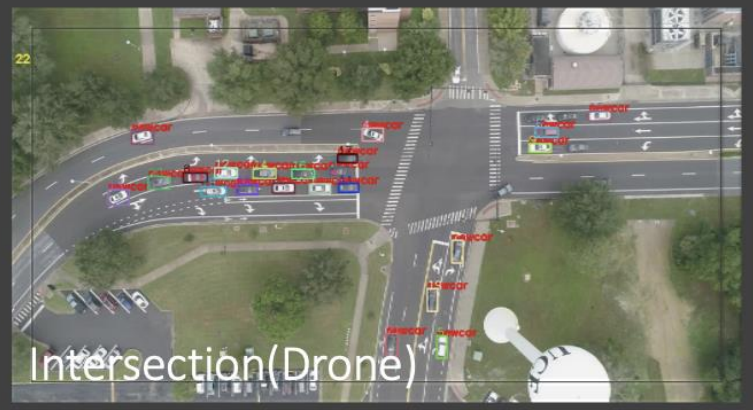
- identify conflicts based on surrogate safety measures



Conflicts Heatmap

- Count
- Volume
- TTC
- PET
- Avg.Speed
- .....

Performance: 0.4 s/f



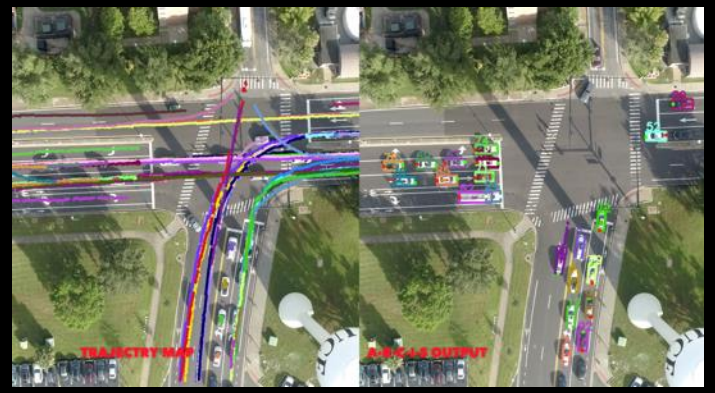
Intersection(Drone)

Expressway(Drone)

Expressway(CCTV)

A.R.C.I.S Cases

DDI-Sarasota-US



Intersection-Orlando-US

Merging area- Najing-China

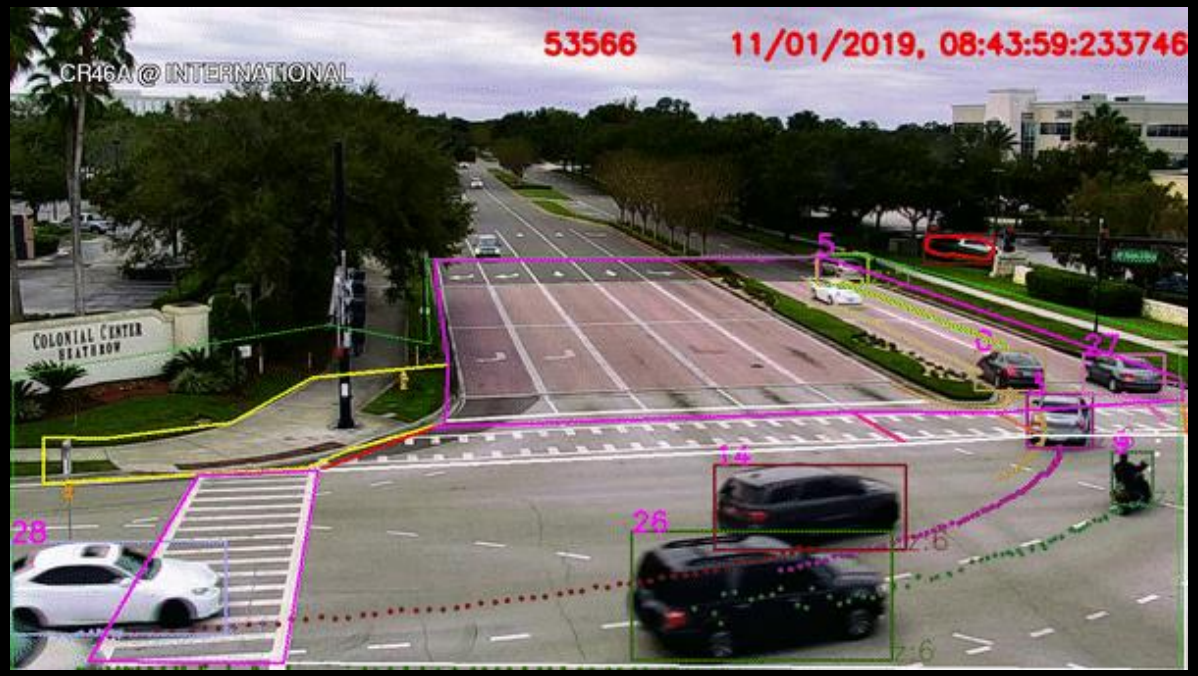
Off ramp-Najing-China

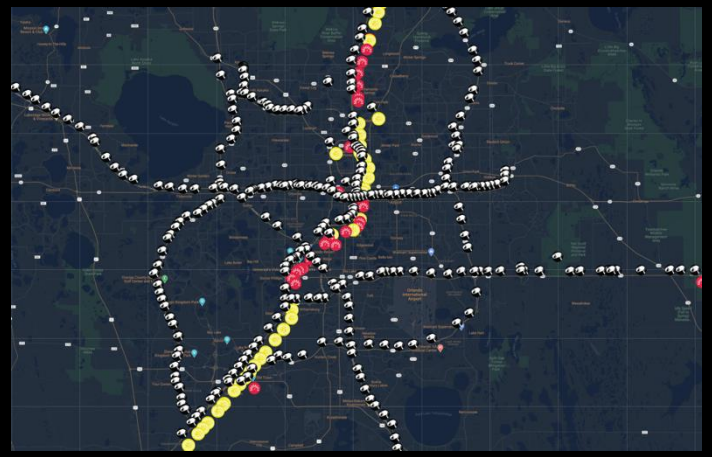
Toll plaza-Nanjing-China

Near Miss Event Detection System (N.M.E.D.S)

UCF SST computer vision platform

Near Miss Event Detection System (N.M.E.D.S)





- Over 600 CCTV cameras

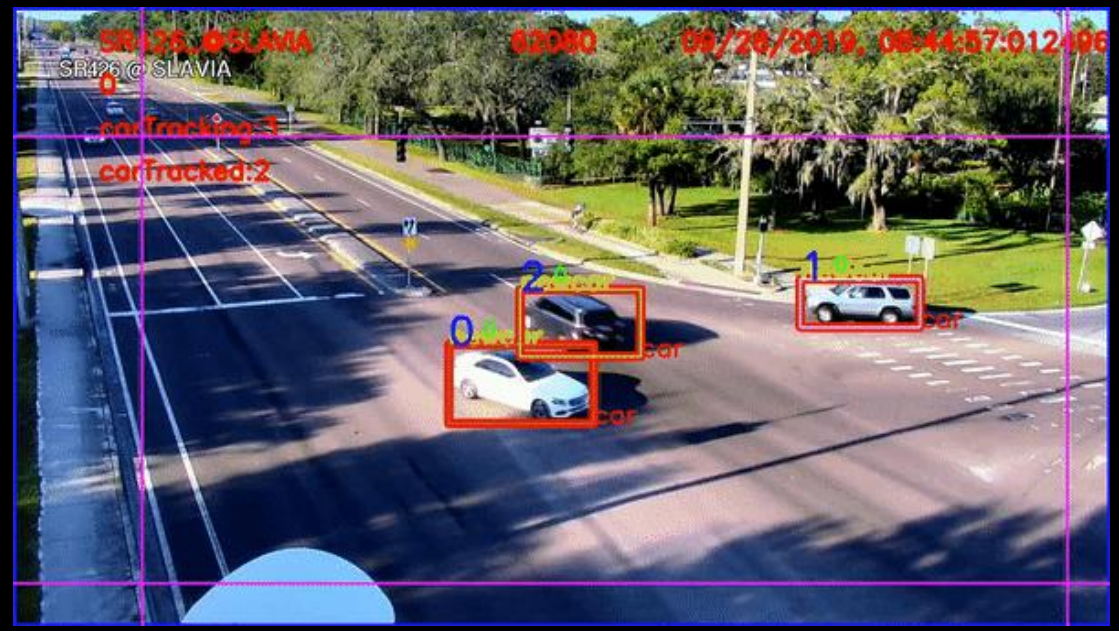
Near Miss Event Detection System(N.M.E.D.S)

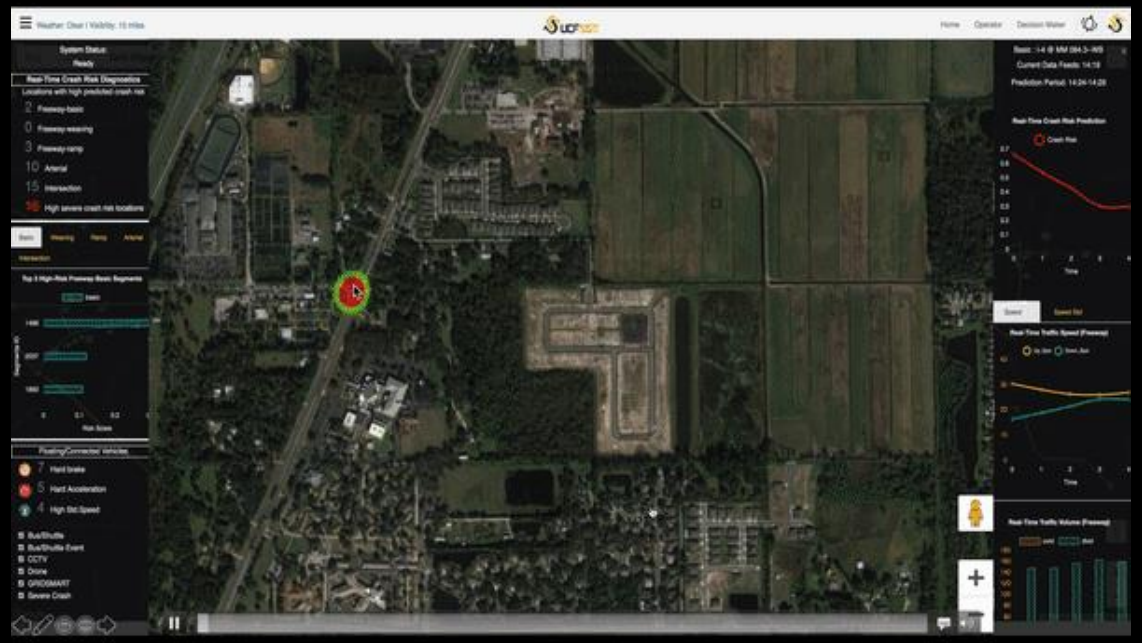
Pedestrian

Red-light running prediction

Pedestrian and bicycle counts
Jaywalk detection

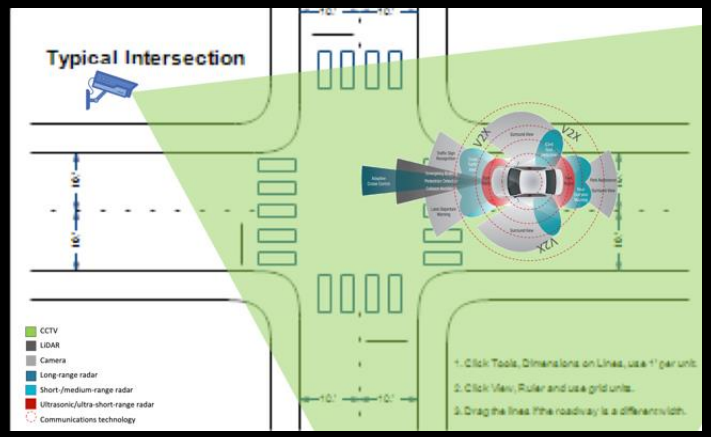
Near Miss Event Detection System (N.M.E.D.S)

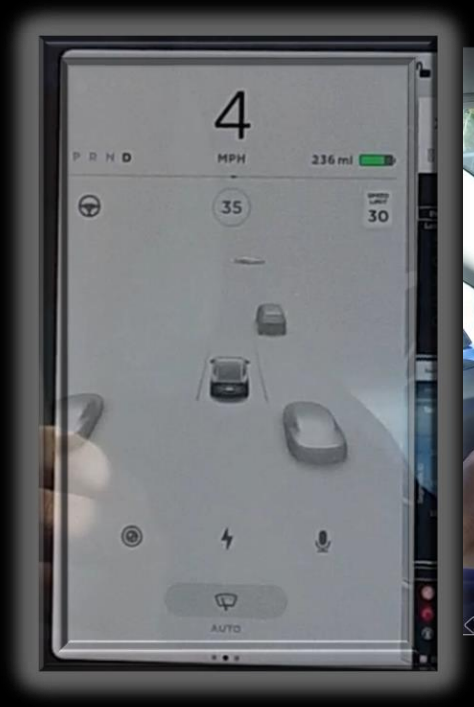


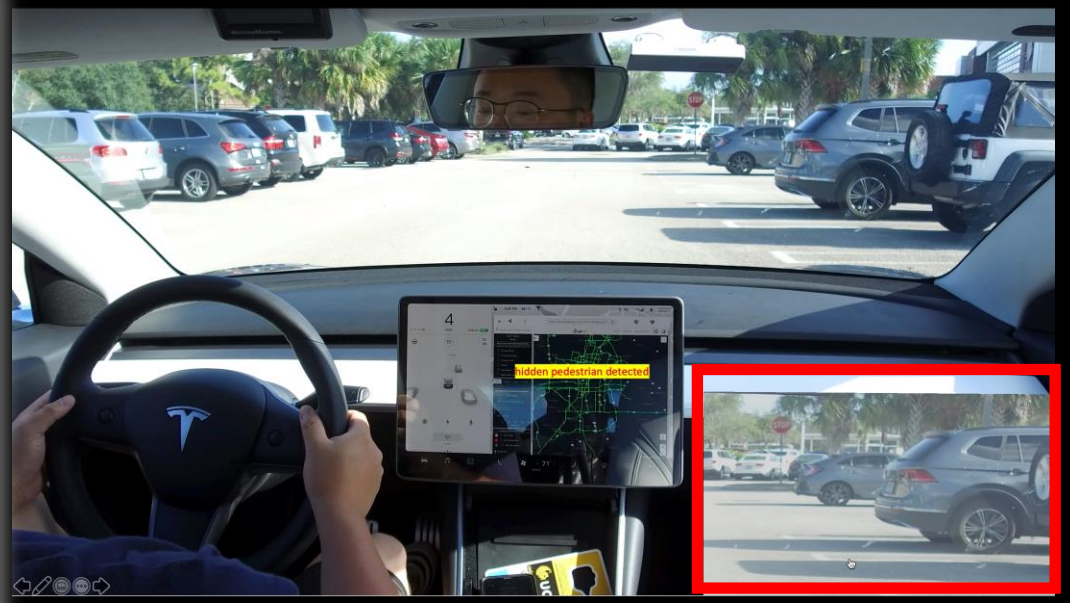


Near Miss Event Detection System (N.M.E.D.S)

I2V



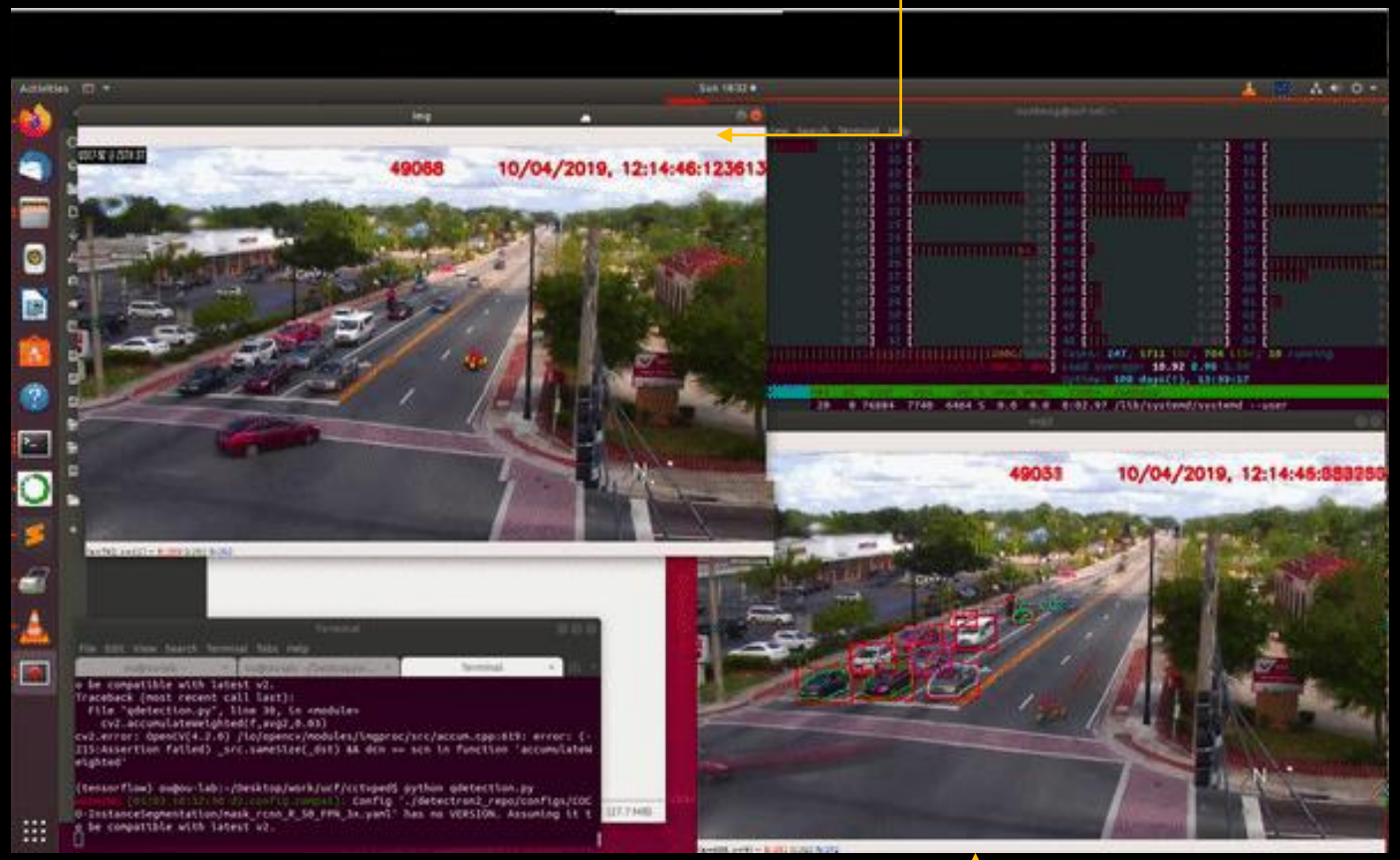




Near Miss Event Detection System (N.M.E.D.S)

Queue

Input CCTV Video



Output number of Queue

- Queue length
- Accumulated weighted frame
  - Removing motion object by calculating the weighted sum of the input image src and the accumulator dst so that dst becomes a running average of a frame sequence
- Semantic segmentation object detection
  - **Occluded vehicle counting**

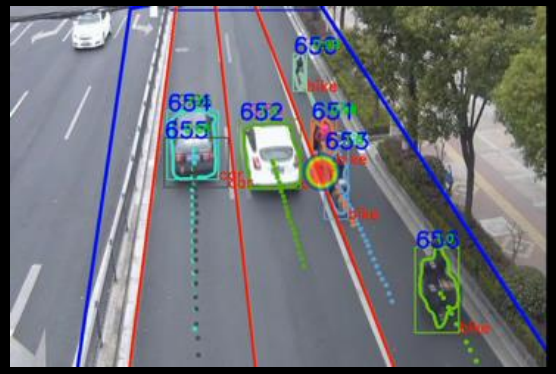
N.M.E.D.S Cases

Traffic Parameters

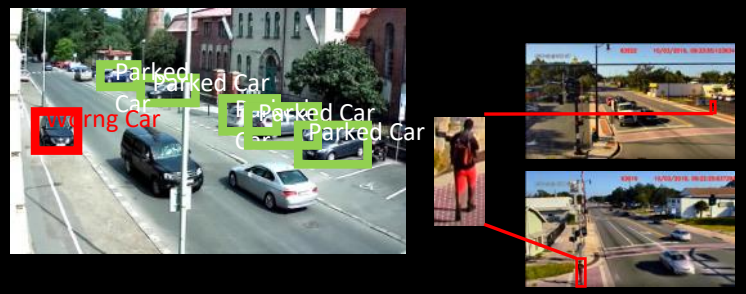
Abnormal event

Parking management

Conflict analysis



Countermeasure effectiveness



Complete Streets

Prediction of Pedestrian Crossing Intention

Proactive Pedestrian Detection System

- The evaluation experiments were conducted at three different intersections
- Nearly 1,000 observations were collected for the evaluation
- The results suggested the proactive pedestrian detection system could detect pedestrians in zones of interest with a high accuracy
- The evaluation results also apply to other areas such as segments and other zones of intersections

Intersection Gemini Blvd & Orion Blvd

Intersection Gemini Blvd & Hydra Ln

Intersection Research Pkwy & Libra Drive

A framework of collision warning system

Detection result	Ground truth		Total
	Presence of pedestrians	No pedestrian	
Presence of pedestrians	388	11	399
No pedestrian	79	484	563
Total	467	495	962
Measurement	Sensitivity=388/467=0.831	Specificity=484/495=0.978	-
	Accuracy = (388+484)/ (388+11+79+484) = 0.906		

Prediction of Pedestrians' Red-Light Crossing Behaviors Using Pose Estimation and Machine Learning

Experiment Results

- Four models were developed:
  - Support Vector Machine (SVM)
  - Random Forest (RF)
  - Gradient Boosting (GBM)
  - eXtreme Gradient Boosting (XGBT)
- RF model achieves the best performance with the AUC value as 0.870.
- The model can be further used in the I2V (infrastructure-to-vehicle) system to better warn drivers.

Modeling Results on the Test Dataset

Model (evaluation metrics)	SVM		RF		GBM		XGBT	
	Walking (red-light phases)	Average	**Walking (red-light phases)**	**Average**	Walking (red-light phases)	Average	Walking (red-light phases)	Average
Precision	0.677	0.709	**0.795**	**0.821**	0.806	0.800	0.707	0.754
Recall	0.488	0.651	**0.721**	**0.843**	0.674	0.808	0.674	0.782
F1-Score	0.568	0.675	**0.756**	**0.828**	0.734	0.798	0.690	0.765
Accuracy	0.840		**0.905**		0.886		0.867	
AUC	0.751		**0.870**		0.861		0.843	

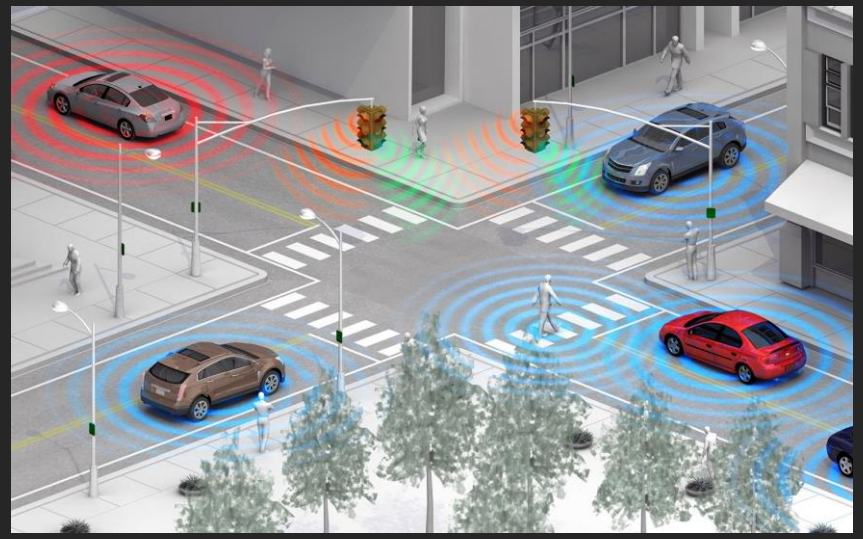


Illustration of warning messages about pedestrians' red-light crossing with the connected vehicle technology

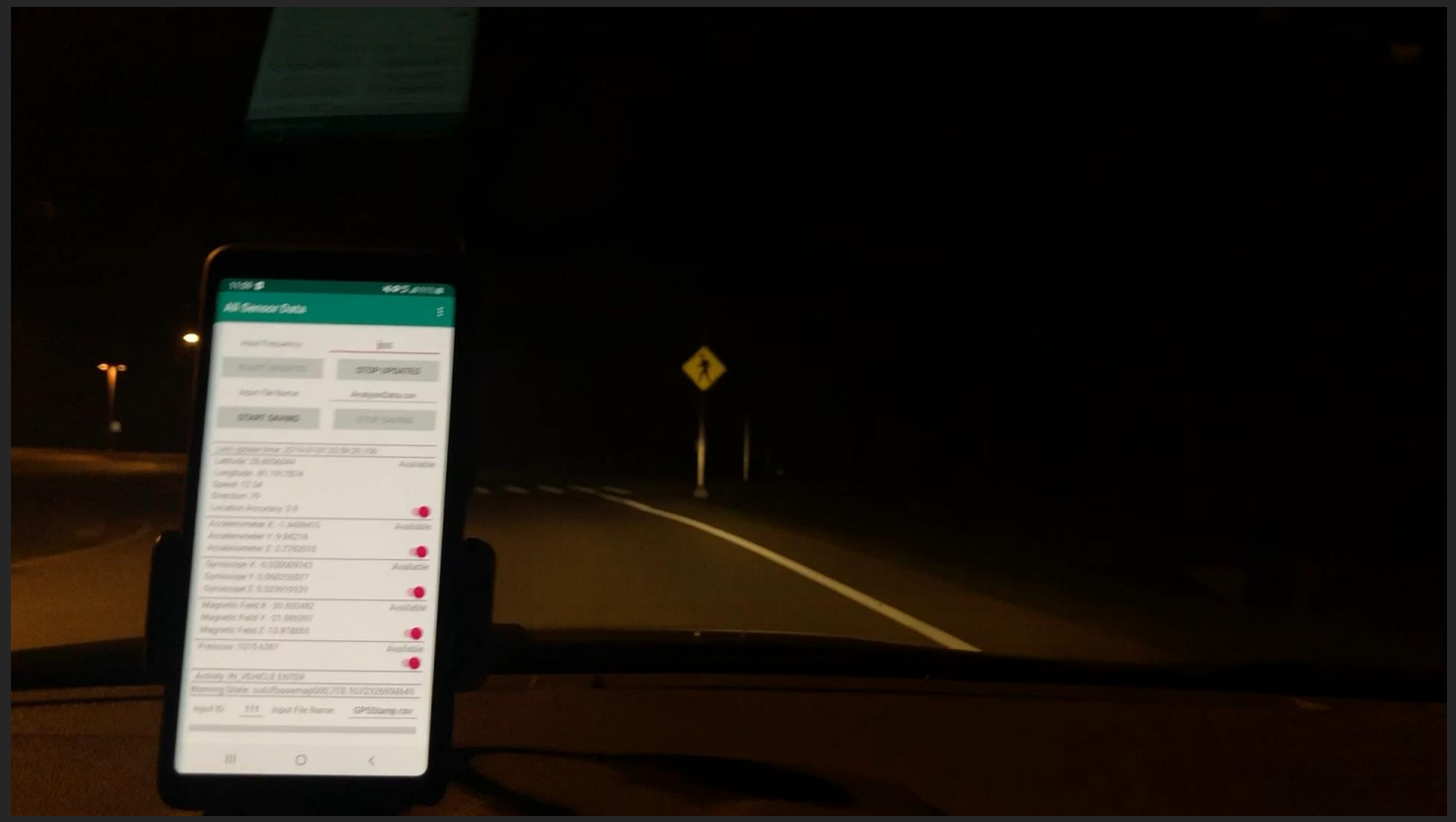
P2V warning – Pedestrians attempt to cross the road at segments

- A pedestrian attempted to cross the road at a segment
- During nighttime, it is difficult for drivers to observe the existence of pedestrians
- Smartphones could send the locations and statuses of the pedestrian and vehicle to the server
- The server determines whether a potential conflict could exist and send the warning to both the pedestrian and driver

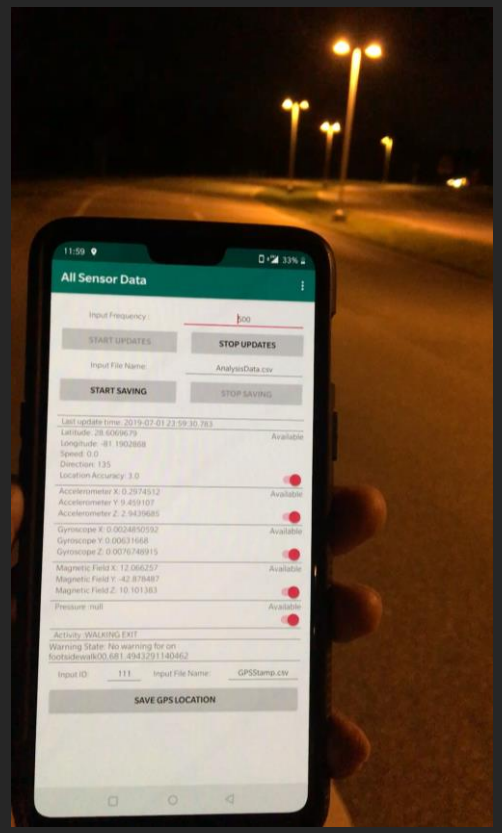
Scenario of the conflict between a jaywalking pedestrian and a vehicle

P2V warning – Pedestrians attempt to cross the road at segments (Jaywalking)

- The pedestrian and driver could receive the warning message at the same time
- The driver could receive the warning before he saw the pedestrian



The driver's view

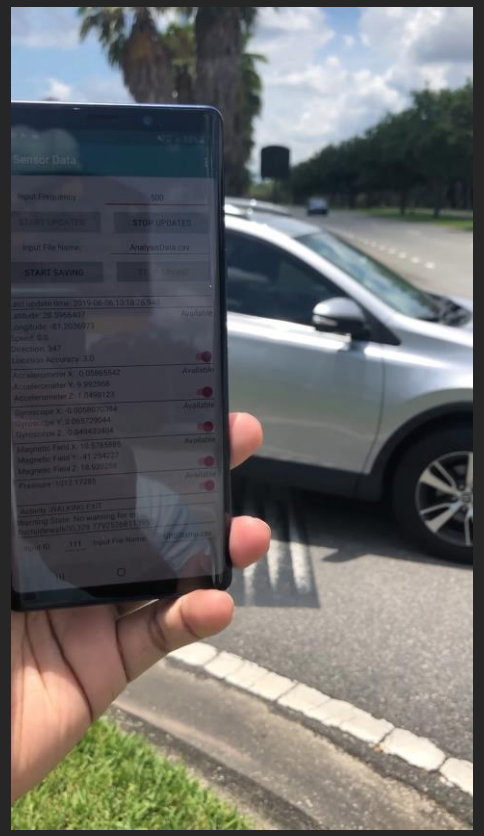


The pedestrian's view

P2V warning – A pedestrian is behind a car

- The driver could receive the warning that the pedestrian ahead who is behind another car

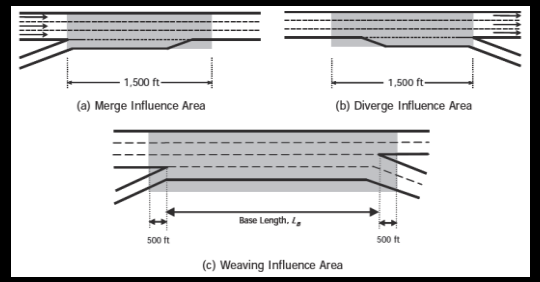
The driver’s view



The pedestrian’s view

Short Term Crash Prediction Models

- Develop short-term crash prediction models to estimate the safety performance of roadways considering geometric, operational, and exposure characteristics for different.
- Include more precise measures of exposure other than AADT, and factors such as speed and speed variability to help predict crashes for varied periods of time/aggregation levels (AM peak, PM peak, off peak, night-time, weekday hourly, and weekend hourly).
- Four models for every sub-scenario, including total crashes (KABCO), fatal and injury crashes (KABC), fatal and severe injury crashes (KA), and property damage only crashes (O).



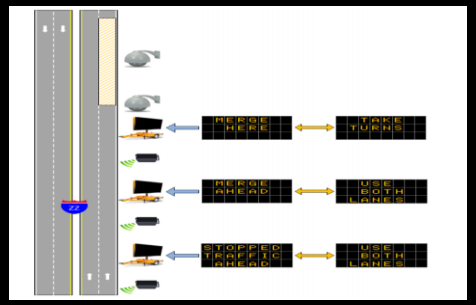
Segment Types
(basic, merge, diverge, weaving, and ramp)

Hard Shoulder Running (HSR)

High-Occupancy Vehicle (HOV) Lane

High Occupancy Toll Lane (HOT)

Reversible Lane (RL)



Work Zone (WZ)

Ramp Metering (RM)

Variable (Advisory) Speed Limit

Adverse Weather

Microscopic and Real-time Data

Example of the Developed Crash Prediction Models

- The following models are developed for Basic Urban segments - fatal and injury crashes (KABC)

AM Peak

	Estimate	Pr(>|z|)
(Intercept)	-0.400	0.484
log_volume	0.331	0.000
log_AvgSpeed	-0.953	0.000
StdSpeed	0.092	0.000
Number of Lanes (Ref. 4)	-	-
Lanes6_8	0.629	0.000
Lanes10_	1.174	0.000
State (Ref. AZ_KS_MI_VA)	-	-
FL_IL	-0.735	0.000
CO_OR_TX	-0.476	0.000
GA	0.669	0.000
MD_WA_WI	-1.276	0.000
AIC	7910.100	
ρ^2	0.082	
MAE (test)	0.371	
MSE (test)	0.708	
MAD (test)	0.489	

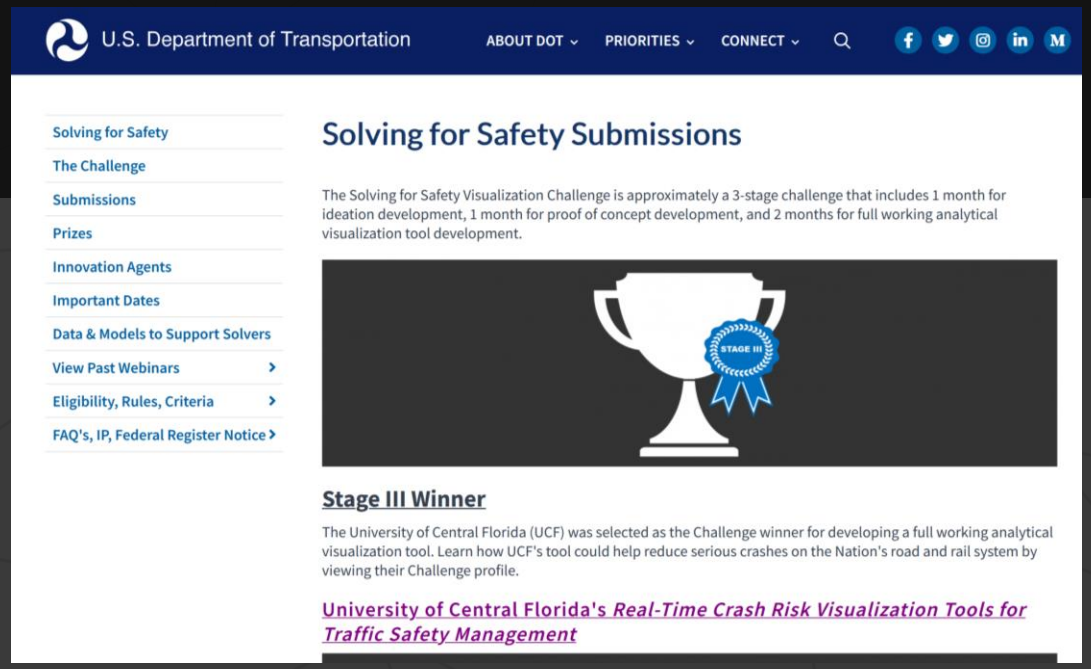
Daytime Off-Peak

	Estimate	Pr(>|z|)
(Intercept)	-0.862	0.055
log_volume	0.319	0.000
log_AvgSpeed	-0.760	0.000
StdSpeed	0.091	0.000
Number of Lanes (Ref. 4)	-	-
Lanes6_8	0.710	0.000
Lanes10_	1.153	0.000
State (Ref. AZ_MI_OR_VA)	-	-
FL_IL_KS	-0.820	0.000
CO_TX	-0.519	0.000
GA	0.621	0.000
MD_WA_WI	-1.225	0.000
AIC	9254.500	
ρ^2	0.085	
MAE (test)	0.462	
MSE (test)	0.962	
MAD (test)	0.608	

AADT

	Estimate	Pr(>|z|)
(Intercept)	0.079	0.841
log_volume	0.433	0.000
log_AvgSpeed	-0.863	0.000
Number of Lanes (Ref. 4)	-	-
Lanes6_8	0.662	0.000
Lanes10_	1.353	0.000
State (Ref. IL_KS_MI_OR_VA)	-	-
AZ_CO_TX	-0.509	0.000
GA	0.858	0.000
FL_WA	-0.815	0.000
MD_WI	-1.089	0.000
AIC	19633.200	
ρ^2	0.065	
MAE (test)	1.936	
MSE (test)	15.617	
MAD (test)	2.715	

Safety Data Initiative (SDI) tool



REAL-TIME CRASH RISK VISUALIZATION

for Operators

UCF-SST

Real-Time Crash Risk

Freeway Arterial

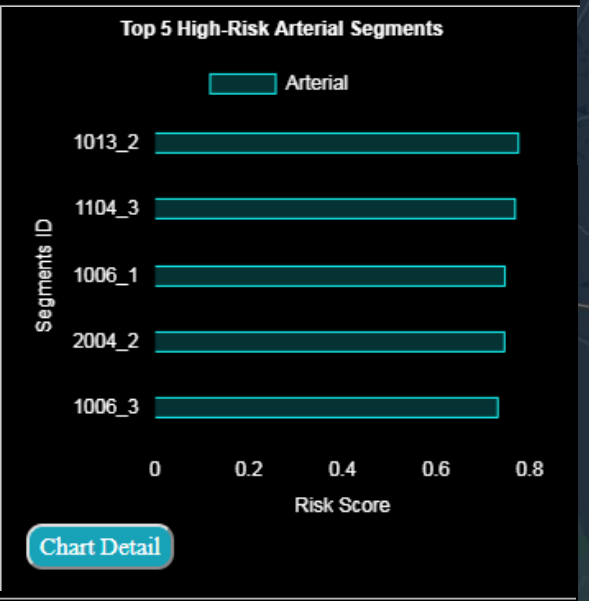
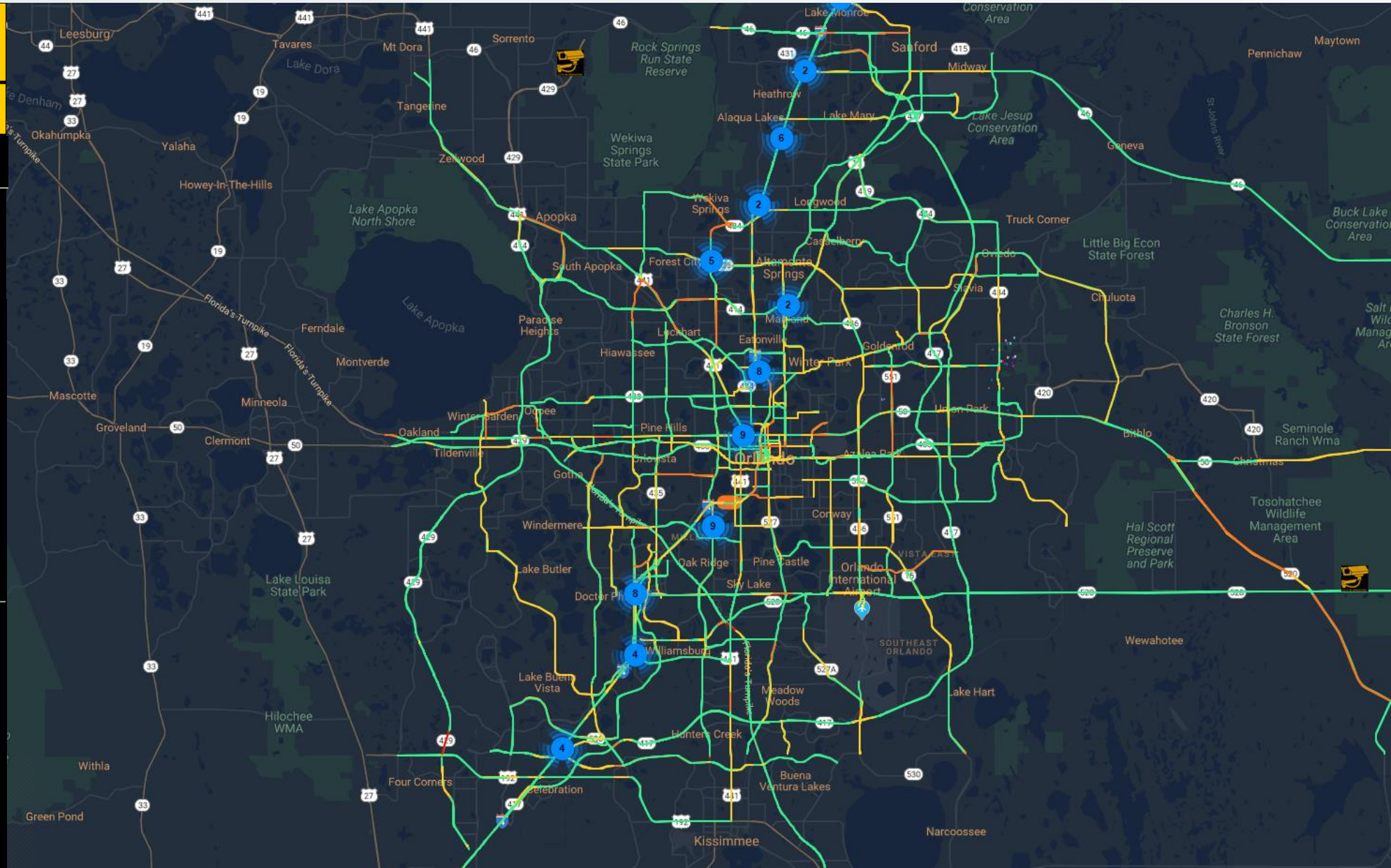


Chart Detail

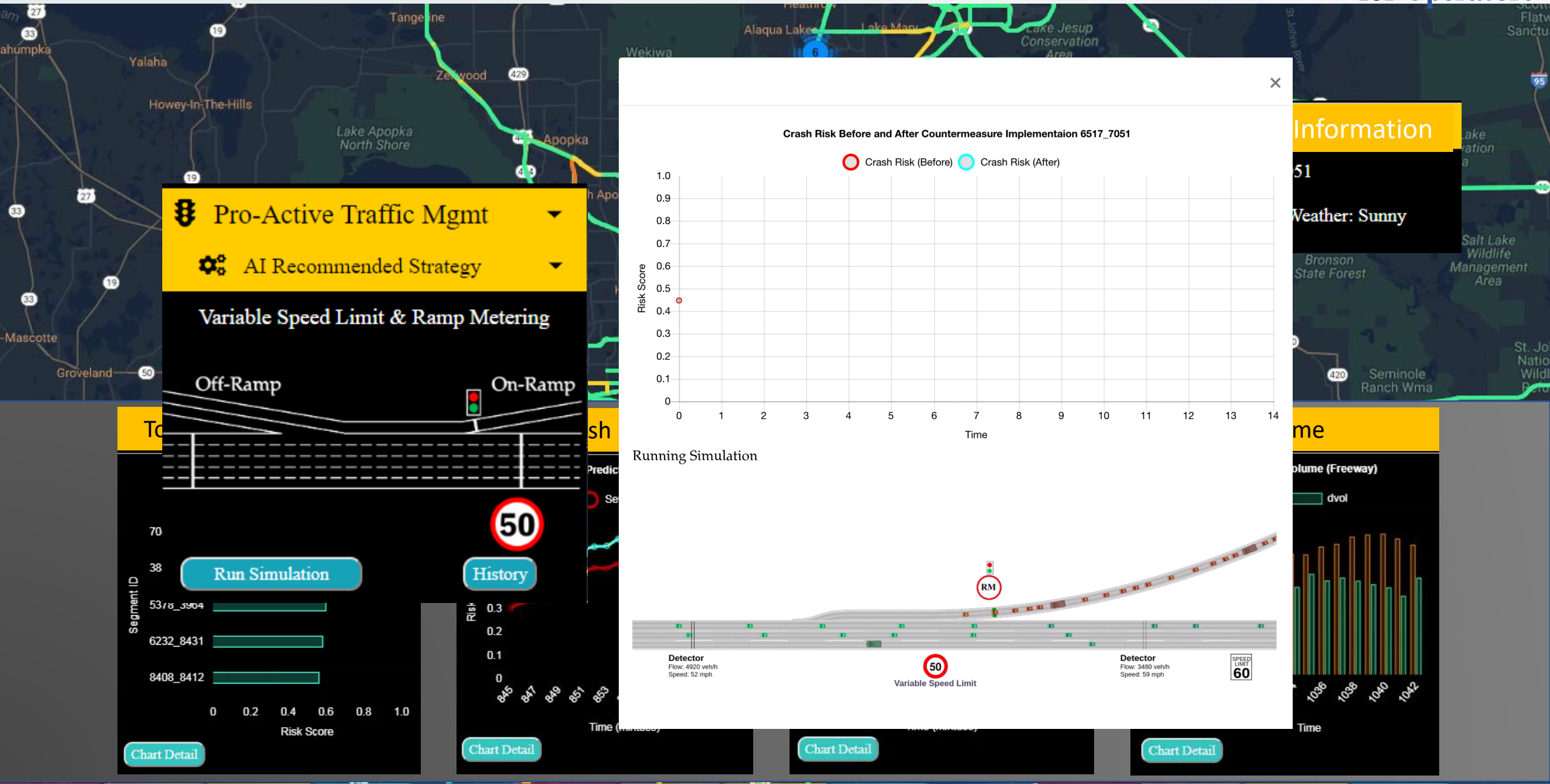
Real-Time Status

Pro-Active Traffic Mgmt



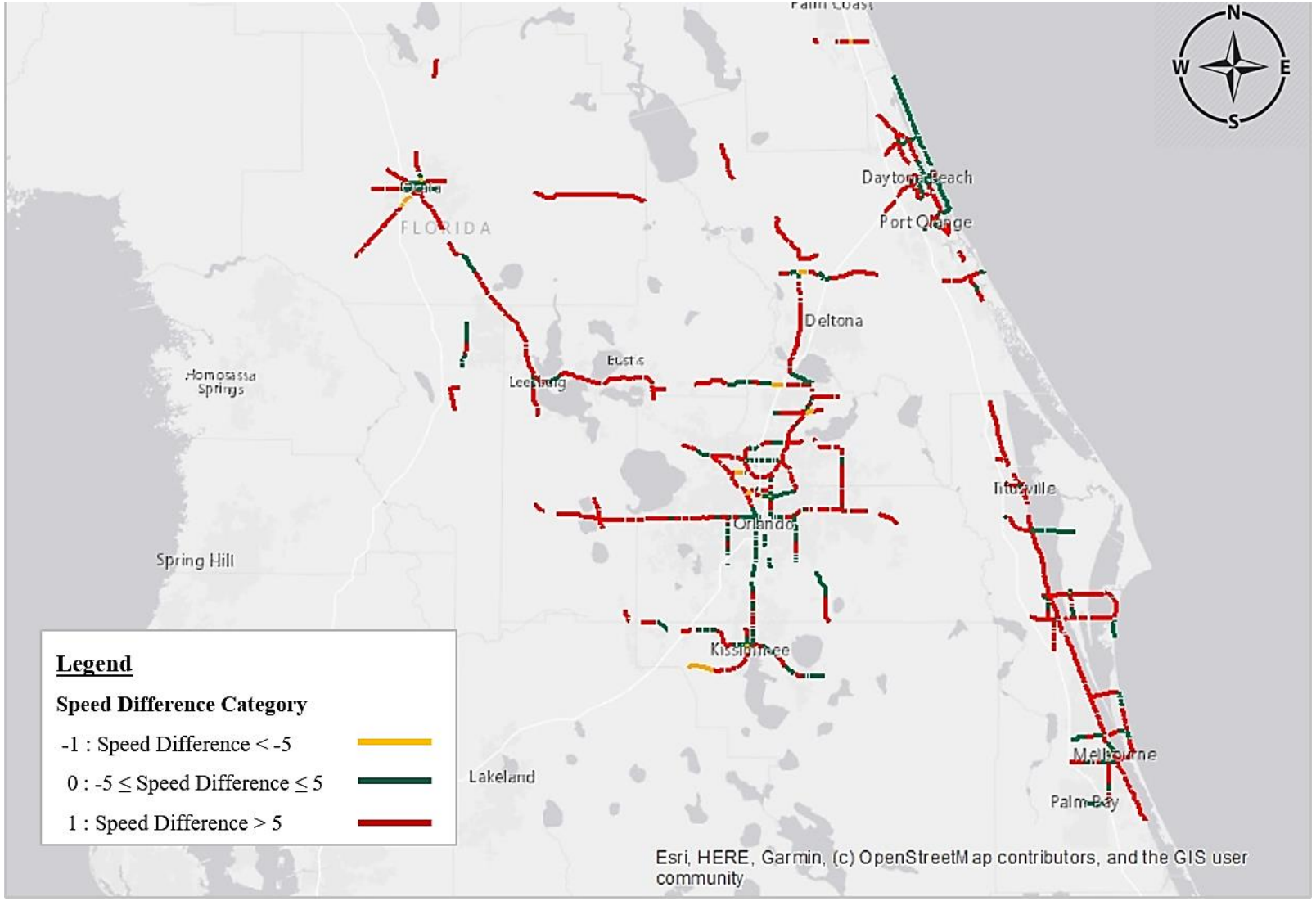
REAL-TIME CRASH RISK VISUALIZATION

for Operators



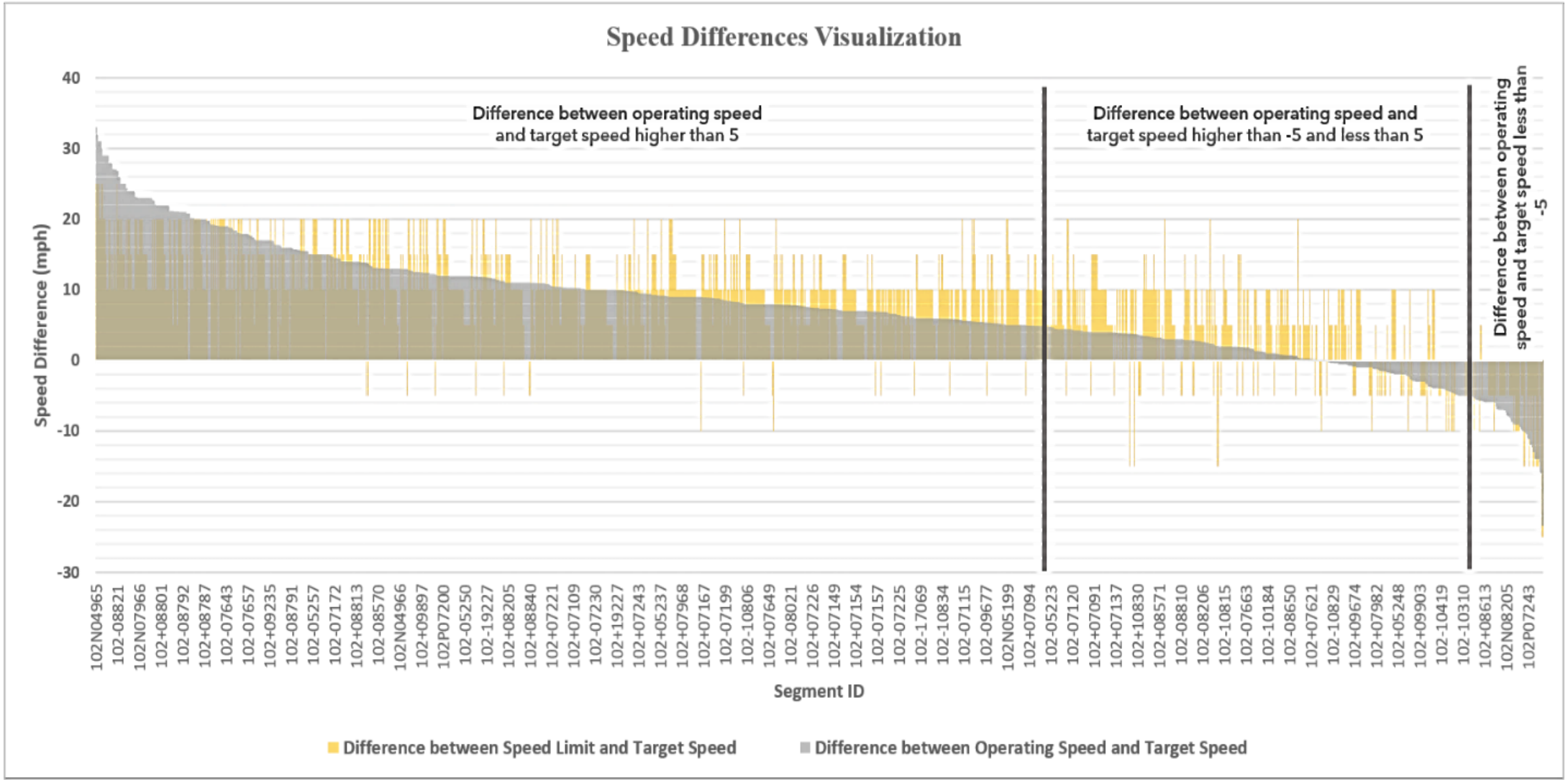
Speed Management

DIFFERENCE BETWEEN OPERATING SPEED AND TARGET SPEED



Study Roadways by Speed Difference Category (C3C, C3R, and C4 Roads)

DIFFERENCE BETWEEN OPERATING SPEED AND TARGET SPEED



Target Speed

Some countermeasures could be implemented to **reduce** the difference between target speed and operating speed: reducing **posted speed limit**, reducing the **inside shoulder width**, constructing **curb and gutter outside shoulder type**, reducing **average block length**, increasing **the width of sidewalks**, and **installing more signalized intersections.**

The results suggested adopting **different posted speed limits** for the **daytime** and **nigh-time periods** to reduce the difference between operating speed and target speed. This will **achieve target speed**, eases the **mobility** and provide **safer roads** for all users in that context (drivers, pedestrians, bicyclists, and public transit users).

UCF

Vision for Transportation

- **More Proactive (but data intensive) approaches / Real-Time**

- **Ever richer information**
  - Smartphones, sensors, onboard vehicle hardware, provide continuous data
  - Traffic status, weather conditions in real-time

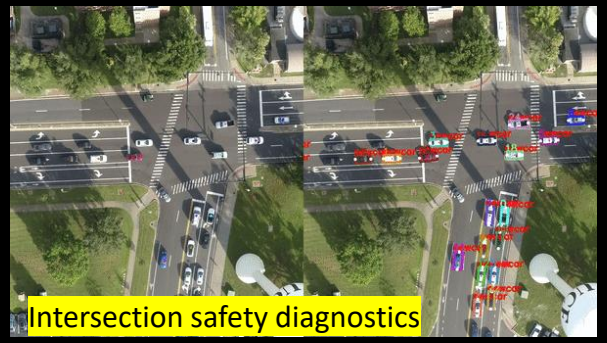
- **Better operation and safety**
  - Bottleneck detection in real-time
  - Crash risk evaluation and prediction in real-time

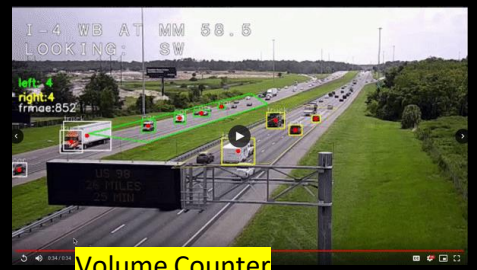
- **More accurate prediction**
  - Formation of congestion, queue length, congestion duration
  - Crash-prone conditions: unstable traffic flow, adverse weather

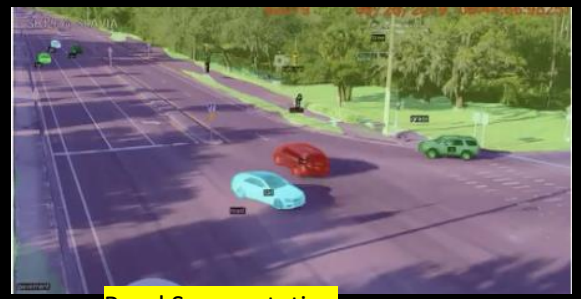
- **Timely communication**
  - Connected Vehicles
  - Media: smartphone, DMS, radio
  - Suggested countermeasures: trip planning, route choice, travel time calculation, VSL, speed advice, etc.

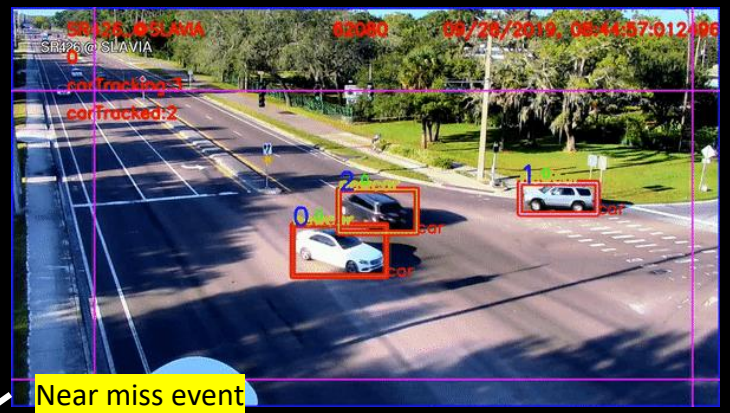
- **Smart Cities' research**
  - FUTURe CITy Initiative: Fostering Smart Urban Transformation and Ubiquitous Resilience with Connected Infrastructure and Technology

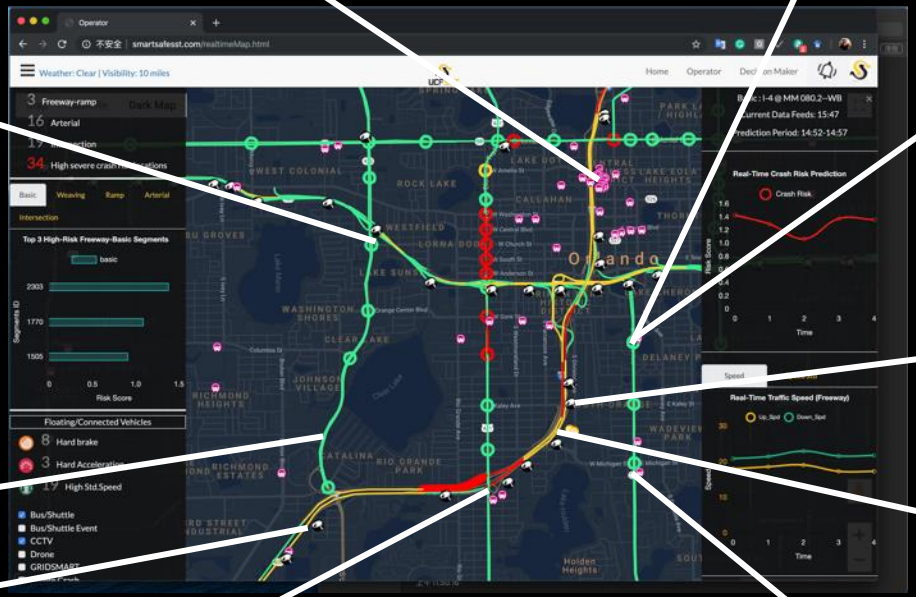
THANK YOU


Intersection safety diagnostics

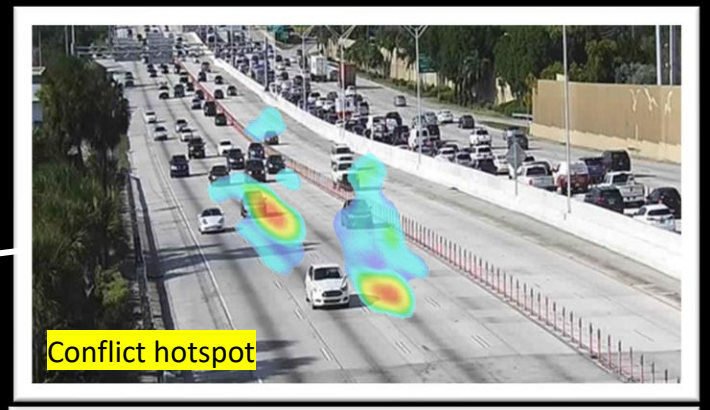

Volume Counter

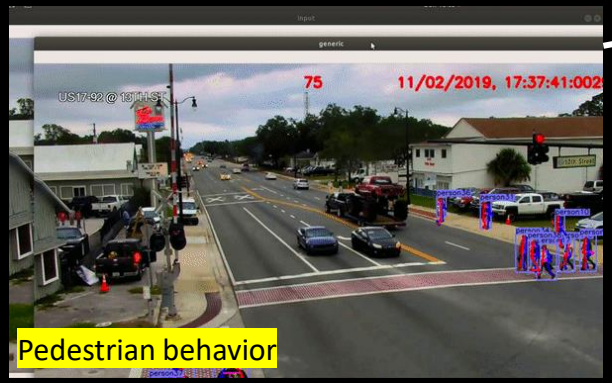

Road Segmentation


Near miss event



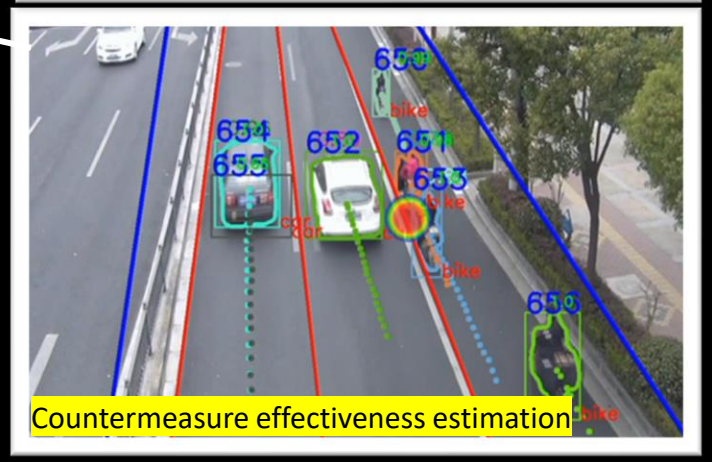
Freeway merging and diverging behavior


Conflict hotspot


Pedestrian behavior

Conflicts identification from 3d bounding box

Cyclist conflicts


Countermeasure effectiveness estimation