Innovations Deserving
Exploratory Analysis Programs

NCHRP IDEA Program

An Automated System for Large-Scale Intersection Marking Data Collection and Condition Assessment

Final Report for
NCHRP IDEA Project 225

Prepared by:
Kun Xie, Hong Yang, and Xiaomeng Dong
Old Dominion University

Hongkai Yu and Huiming Sun
Cleveland State University

December 2022

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AN AUTOMATED SYSTEM FOR LARGER-SCALE INTERSECTION MARKING DATA COLLECTION AND CONDITION ASSESSMENT

NCHRP IDEA Program Final Report

IDEA Project NCHRP-225

Prepared for

The NCHRP IDEA Program
Transportation Research Board
National Academies of Sciences, Engineering, and Medicine

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GLOSSARY

AASHTO	American Association of State Highway and Transportation Officials
AI	Artificial Intelligence
ANN	Artificial neural network
API	Application Programing Interface
BBAVectors	Box Boundary-Aware Vectors
CVAT	Computer Vision Annotation Tool
DOTA	Large-scale dataset for object detection in aerial images
DOT	Departments of Transportation
FAST	Fixing America's Surface Transportation Act
GIS	Geographic information systems
GUI	Graphical user interface
HSIP	Highway Safety Improvement Program
HSM	Highway Safety Manual
HTML	Hyper Text Markup Language
ID	Identity document
IoT	Internet of Things
IT	Information Technology
ITS	Intelligent Transportation Systems
KNN	K-nearest neighbors
MAP-21	Moving Ahead for Progress in the 21st Century Act
MIRE	Model Inventory of Roadway Elements
MUTCD	Manual on uniform Traffic Control Devices
R-CNN	Region-based Convolutional Neural Networks
RGB	Red, green, and blue
SVM	Support vector machine
T1	Transverse crosswalk
T2	Zebra crosswalk
T3	Ladder crosswalk
VGG16	Convolutional neural network with 16 layers deep

EXECUTIVE SUMMARY

Intersection markings play a vital role in providing road users with guidance and information. The conditions of intersection markings will be gradually degrading due to vehicular traffic, rain, and/or snowplowing. Degraded markings can confuse drivers, leading to increased risk of traffic crashes. Timely obtaining high-quality information of intersection markings lays a foundation for making informed decisions in safety management and maintenance prioritization. However, current labor-intensive and high-cost data collection practices make it very challenging to gather intersection data on a large scale.

This IDEA project develops an automated system to intelligently detect and characterize intersection markings and to assess their degradation conditions with existing roadway Geographic information systems (GIS) data and aerial images. The system focuses on two types of markings at intersections – lane-use arrows and crosswalks, while it has the flexibility to be extended to cover other road markings as well. The seamless integration of spatial analytics and advanced computer vision techniques makes the proposed system truly cost-effective, scalable, and computationally efficient. The system harnesses emerging artificial intelligence techniques such as transfer learning and multi-task deep learning to enhance its robustness, accuracy, and computational efficiency. A data acquisition module was developed to automatically retrieve intersection locations from roadway GIS data in Virginia and capture corresponding aerial images on a large scale. Over 3,000 intersection images have been captured and manually annotated. Marking images were synthesized from different environment settings, and the synthesized data was used in a transfer learning process to pre-train computer vision models for marking detection and characterization. Computer vision modules were developed to detect and classify lane-use arrows (85% average precision) and crosswalks (89% average precision), to reliably measure the marking sizes by calibrating detection bounding boxes, and to assess the degradation conditions of markings (91% overall accuracy for lane-use arrows and 83% for crosswalks). Data acquisition and computer vision modules developed were integrated and a graphical user interface (GUI) was built for the system. The developed system is deployed as a web-based application so that it does not require powerful client computers and any users with internet connections can easily access it.

The proposed system can fully automate the processes of marking data collection and condition assessment on a large scale with almost zero cost and short processing time. The seamless integration of spatial analytics and advanced computer vision techniques makes the system truly cost-effective, scalable, and computationally efficient. Current data collection practices require state agencies to invest millions of dollars in contracting very time-consuming data collection services each year. By economically providing large-scale intersection marking data, this system can enable state agencies to empower analytic methods for data-driven safety management and timely assist maintenance prioritization for reinforcing intersection safety.

IDEA PRODUCT

This IDEA project develops an automated system for large-scale intersection marking data collection and condition assessment. FIGURE 1 illustrates the conceptual design of the system. The system focuses on two types of markings at intersections – lane-use arrows and crosswalks, while it has the flexibility to be extended to cover other road markings as well. The system economically utilizes roadway geographic information systems (GIS) data and aerial images as inputs, which are commonly available from state department of transportations (DOTs) or open sources. The use of GIS data enables fast indexing and identification of intersections and accelerate the process of aerials image data extraction, making the proposed approach truly scalable and computationally efficient. The extracted intersection image data were used to train a novel computer vision model for detection, characterization, and condition assessment of intersection markings. Emerging artificial intelligence techniques were harnessed to improve accuracy, robustness, and computational efficiency of the system. This system will be the foundation of future expansions to collect other roadway features such as medians and driveways to support additional data needs of DOTs.

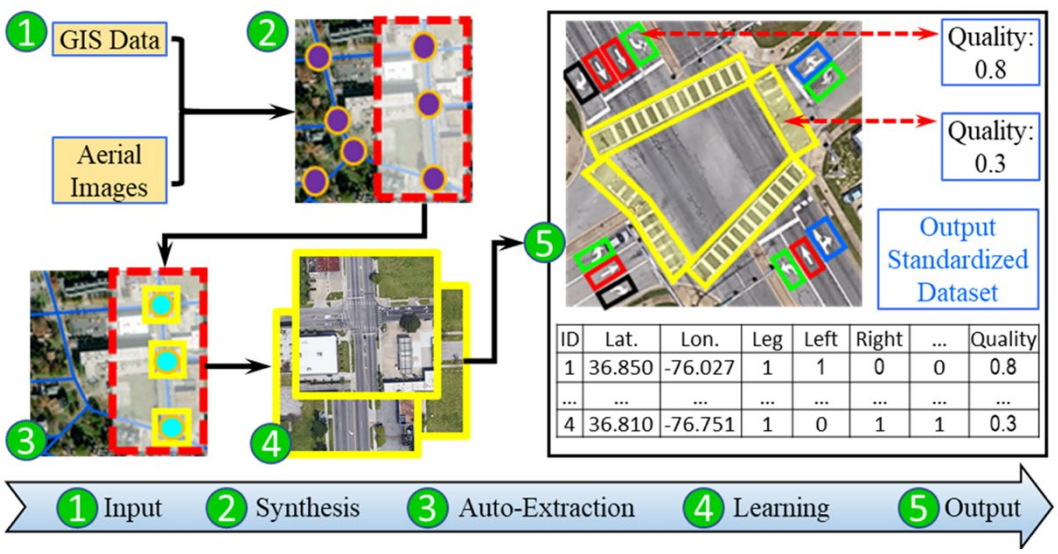


FIGURE 1 Conceptual illustration of the automated system for intersection marking data collection.

CONCEPT AND INNOVATION

Motivation

The Model Inventory of Roadway Elements (MIRE) program of Federal Highway Administration (FHWA) emphasizes that roadway data, including intersection markings, are critical to data-driven safety management *(1)*. However, MIRE has identified that existing roadway inventories have large gaps in

intersection marking data such as the number of exclusive left-turn lanes and the presence of crosswalks *(2)*. Intersection markings play a vital role in providing road users with guidance and information. The conditions of intersection markings will be gradually degrading due to vehicular traffic, rain, and/or snowplowing. Degraded markings can confuse drivers, leading to increased risk of traffic crashes. Timely obtaining high-quality information of intersection markings lays a foundation for making informed decisions in safety management and maintenance prioritization. However, current labor-intensive and high-cost data collection practices make it very challenging to gather intersection data on a large scale. *(3)*. It immediately requires a cost-effective tool that can accurately and efficiently collect statewide intersection marking data.

Potential Payoff for Practice

The system can fully automate the processes of marking data collection and condition assessment on a large scale with almost zero cost and short processing time (e.g., in a preliminary test, the processing time per intersection is less than 2 second). The system can help states improve their inventory databases to accommodate data requirements legislated in the Moving Ahead for Progress in the 21st Century (MAP-21) Act and the Fixing America's Surface Transportation (FAST) Acts. More specifically, the large-scale data produced through the developed system can greatly benefit transportation agencies in several key aspects:

1) **Advances intersection safety management**. The system can provide state DOTs demanding data for Highway Safety Improvement Program (HSIP). The availability of large-scale intersection marking data (e.g., presence of crosswalks, dedicated left-turn lanes, etc.) enables agencies to use the analytic methods provided in the American Association of State Highway and Transportation Officials' (AASHTO's) Highway Safety Manual (HSM). It helps bridge the gaps in current modeling practices by offering critical data to support safety decision making in hotspot identification and before-after safety evaluation.
2) **Improves the inventory of roadway data elements**. The system offers a cost-effective tool to improve existing roadway inventory databases and provide additional data elements needed to support MIRE.
3) **Enables infrastructure maintenance prioritization**. It is estimated that state agencies spend more than $1 billion annually in maintaining road markings in the United States and Canada *(4)*. The developed system can allow agencies to monitor the conditions of a large number of markings for better allocation of resources and timely maintenance.

4) **Augments intelligent transportation systems (ITS)**. The developed system can produce detailed intersection profiles for supporting ITS applications such as the development of high-resolution digital maps, driver-assistance systems, and safety warning systems.
5) **Supports transportation planning modeling**. The generated intersection data can help transportation planners develop more accurate planning models by incorporating detailed information on intersection configurations.

Existing Approaches and Their Limitations

Though road marking data are often collected manually in practice, there are attempts to leverage image processing techniques (e.g., edge detection) to detect road markings *(5-7)*. Despite faster proceeding speeds, those approaches rely on empirical functions that are often difficult to be generalized in varying environments *(8)*. More adaptive learning-based methods such as k-nearest neighbors (KNN) *(9)*, support vector machine (SVM) *(10)*, random forest *(11)* and artificial neural network (ANN) *(12)* are experimented. However, most learning-based methods for marking recognition are customized for driving assistance, with only small and local data processed rather than large-scale data collection. Additionally, most existing approaches are still sensitive to noises caused by occlusion, illumination variations, and degraded conditions. Furthermore, condition assessment of intersection markings is still under-examined. Finally, no integrated approach is available to recognize marking and assess degradation condition concurrently. Thus, there is an immediate need to develop a more optimal and economical solution for marking data collection on a large scale.

Innovation

The system has innovatively addressed the limitations of existing data collection approaches from the following aspects:

1) **Seamless integration of spatial analytics with computer vision techniques.** Computer vision techniques have the advantages in recognizing visual patterns but are not helpful in quickly locating the intersections. Spatial analytics helps pinpoint intersections in the target area and auto-extract their aerial images. Incorporating the spatial information can be the catalyst to greatly reduce the efforts in image segmentation and object recognition, and thus it makes the data collection process truly scalable and computationally efficient.
2) **Embedding transfer learning for more robust and accurate outcomes.** The system has transfer learning capability to robustly detect and characterize intersection markings in varying environments, e.g., occlusion, illumination variations, degraded conditions, etc. It synthesizes a large set of markings under various scenarios to augment the model's ability to learn from the real data.

3) **Smart application of deep learning for condition assessment.** Humans are sensitive to visual impairments of markings, but it is very costly to apply subjective assessment on a large scale. The system leverages deep learning to generate quality scores consistent with human viewers. The multi-scale deep features of markings are fed into a regression sub-network to produce quality scores to indicate their degradation conditions.
4) **Multi-task learning for higher accuracy and computational efficiency.** The system creatively performs the joint tasks of intersection marking detection, characterization, and condition assessment in an end-to-end deep learning model. Model can better learn a new task by transferring the knowledge it has acquired by learning a related task. The simultaneous accomplishment of multiple tasks ensures its computational efficiency and inference performance for large-scale data collection practices.
5) **Enhanced system accessibility and reproducibility.** Despite the equipped advanced spatial analytics and Artificial Intelligence (AI) components, the system has no prerequisite of knowledge and skills in imaging processing and GIS tools, and therefore enables more users to access it. In addition, it provides objective measurements for reproducible data collection.

INVESTIGATION

Extraction and Annotation of Intersection Aerial Images

A web-based tool was developed for downloading satellite images using Mapbox base-map. As shown in FIGURE 2, the developed web tool looped through each intersection (using shapefiles as inputs) and downloaded corresponding aerial images. Meanwhile, the Identity document (ID) and coordinates attributes of the images were stored as references of their geo-locations.

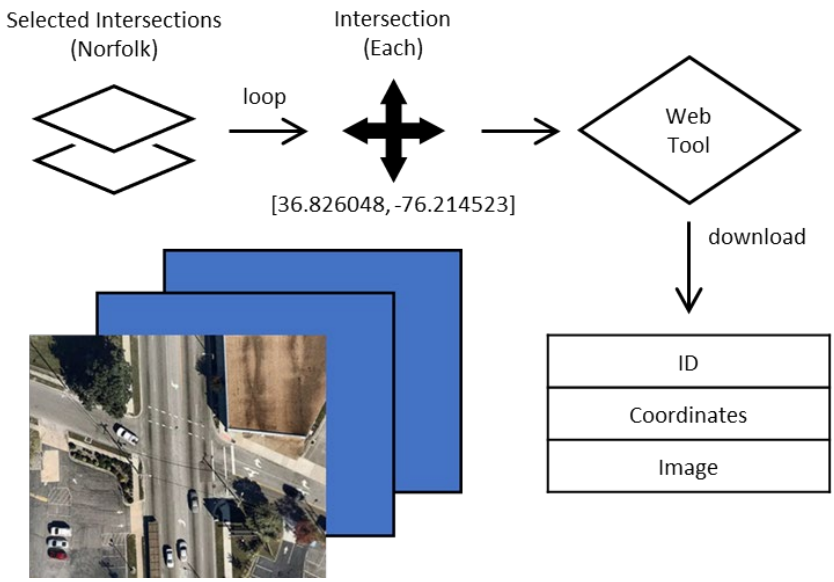


FIGURE 2 Workflow for downloading intersection aerial images.

An annotation tool of Computer Vision Annotation Tool (CVAT) was tested and used to manually label the types of lane-use arrows (i.e., left, right, left & straight, right & straight, and straight) and crosswalks (i.e., transverse, zebra, and ladder) and their degradation conditions (i.e., low-quality and high-quality). An example of annotation is shown in FIGURE 3.

FIGURE 3 Overall annotated image with land-use arrows, crosswalks, and degradation conditions labeled.

Marking Detection

Detect Lane-use Arrows

The downloaded aerial images from Mapbox were divided into a training set to train computer vision models and a testing set to test the trained model for performance evaluation. Each aerial image is a 3-channel Red, green, and blue (RGB) color image with a rough resolution of 1354×967 pixels. The lane-use arrows of each image were also manually annotated. TABLE 1 presents the statistical information of the lane-use arrow data distribution in the dataset.

TABLE 1 Lane-use Arrow Data Distribution in the Collected Dataset

Traffic Markers	Total No.	No. in Training Set	No. in Testing Set
Left	4,089	3,248	841
Left & Straight	522	446	76
Straight	1,136	860	276
Right	2,399	1,920	479
Right & Straight	676	550	126
Sum	8,822	7,024	1,798

The Faster RCNN model *(13)* was used to detect and classify lane-use arrows in the satellite images. The network structure is shown in FIGURE 4. The backbone to extract image feature is the convolutional neural network with 16 layers deep (VGG16) *(14)*.

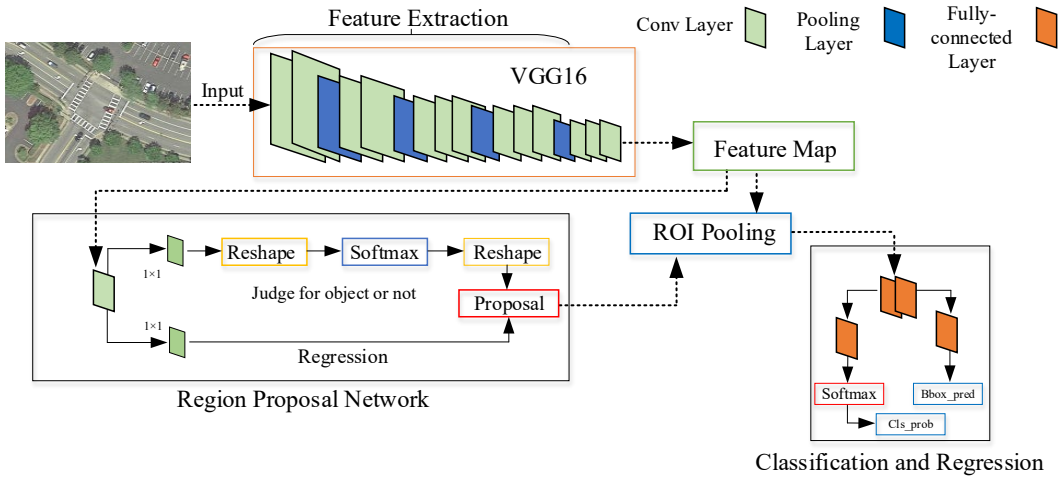
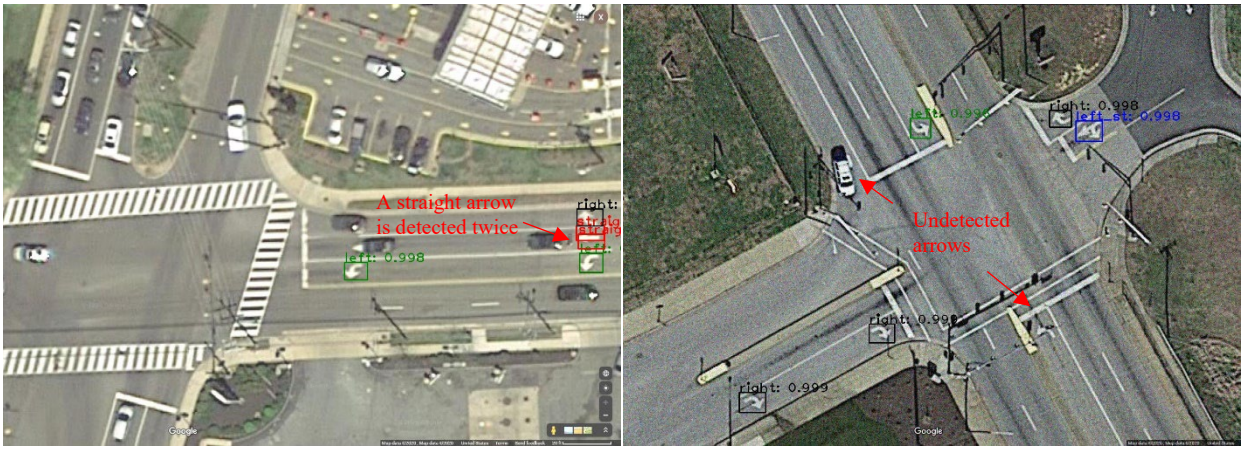


FIGURE 4 Faster RCNN model for lane-use arrow detection.

After training the Faster RCNN model on the training set, the detection performance was evaluated on the testing set. Examples of correctly detected and incorrectly detected (e.g., misclassification, missing) lane-use arrows are presented in FIGURE 5 (refer to the APPENDIX for more detection results). Common metrics for object detection, *i.e.*, precision, recall, F-measure, and average precision[1] were used to evaluate the performance of each lane-use arrow class, with results reported in TABLE 2. The overall average precision reaches 80% on the testing set.

(a) Correctly detected lane-use arrows



(b) Incorrectly detected lane-use arrows

FIGURE 5 Example of correctly detected and incorrectly detected lane-use rrows. (Numbers indicate confidence levels)

[1] Aka Area Under the Precision-Recall Curve. Average precision indicates whether your model can correctly identify all the positive examples without accidentally marking too many negative examples as positive.

TABLE 2 Lane-use Arrow Detection Performance on the Testing Set

Lane-use Arrows	Precision	Recall	F-measure	Average Precision
Left	0.63	0.80	0.70	0.89
Left & Straight	0.34	0.80	0.48	0.63
Straight	0.51	0.85	0.64	0.91
Right	0.51	0.85	0.59	0.80
Right & Straight	0.40	0.81	0.54	0.66
Mean	0.46	0.82	0.59	0.78

(Note: Each metric is ranged between 0 to 1 and higher is better.)

Detect Crosswalks

Over 3,000 aerial images of intersections with crosswalks were collected, which were subsequently divided into a training set to develop the deep learning model and a testing set to evaluate the model performance. Each aerial image is a three-channel RGB color image with a resolution of 1354×967 pixels. All the crosswalks on these images were manually annotated. The crosswalks were classified into three types according to the Manual on Uniform Traffic Control Devices (MUTCD) standards as shown in FIGURE 6. TABLE 3 presents the statistical information of the crosswalks in the collected dataset.

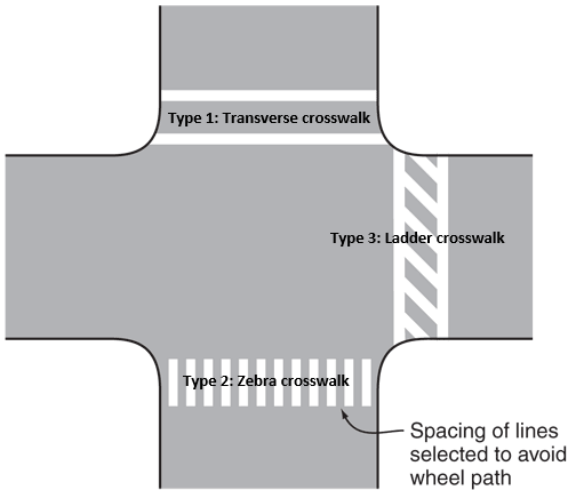


FIGURE 6 Examples of crosswalk markings. (T1 - Transverse Crosswalk: crosswalk marker with two parallel solid white lines; T2 - Zebra Crosswalk: crosswalk marker with a series of closely spaced solid white lines; T3 – Ladder Crosswalk: crosswalk marker with solid white lines between two parallel solid white lines)[2]

[2] Source: https://mutcd.fhwa.dot.gov/htm/2009/part3/fig3b_19_longdesc.htm

TABLE 3 Crosswalk Data Distribution in the Collected Dataset

Crosswalk Type	Total No.	No. in Training Set	No. in Testing Set
T_1 - Transverse Crosswalk	4,974	3,997	977
T_2 - Zebra Crosswalk	2,437	1,947	490
T_3 - Ladder Crosswalk	1238	975	263
Sum	8,649	6,919	1,730

Most crosswalk markings are arbitrary-oriented, horizontal bounding boxes used for the detection of lane-use arrows are no longer suitable. A new deep learning model capable of detecting rotated objects is needed. The Box Boundary-Aware Vectors (BBAVectors) model *(15)* was used for oriented object detection in aerial images with Box Boundary-Aware Vectors. The BBAVectors model resulted in an outstanding performance in the Large-scale dataset for object detection in aerial images (DOTA) dataset *(16)*, which is a benchmark dataset for oriented object detection in computer vision. The network structure of BBA Vectors is shown in FIGURE 7.

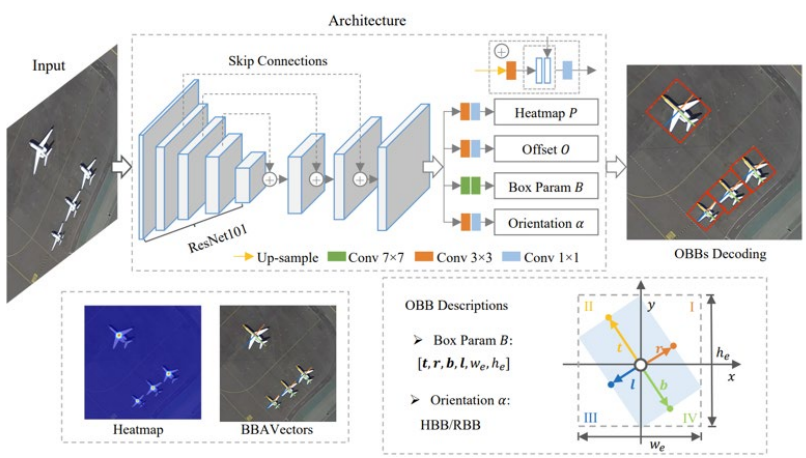
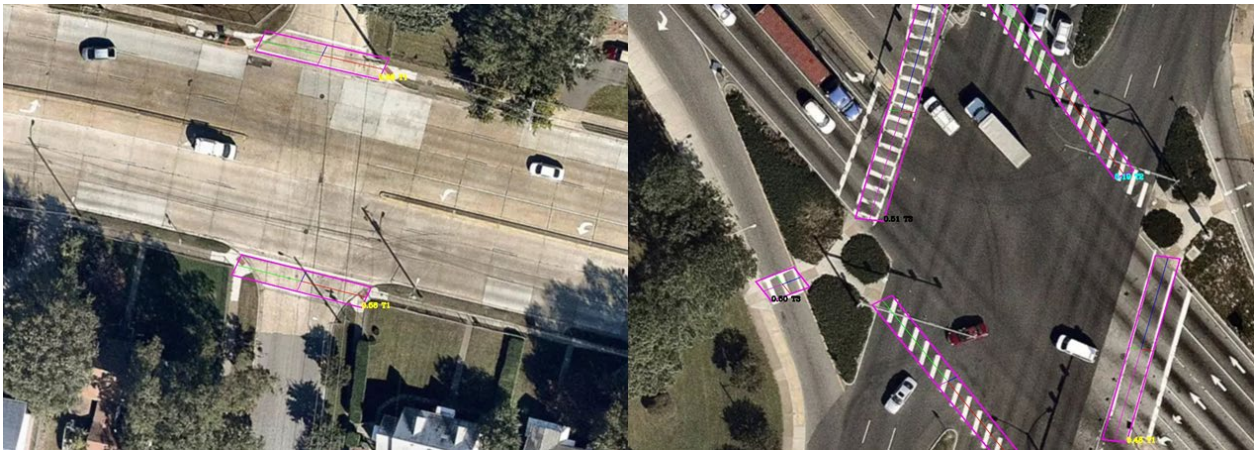
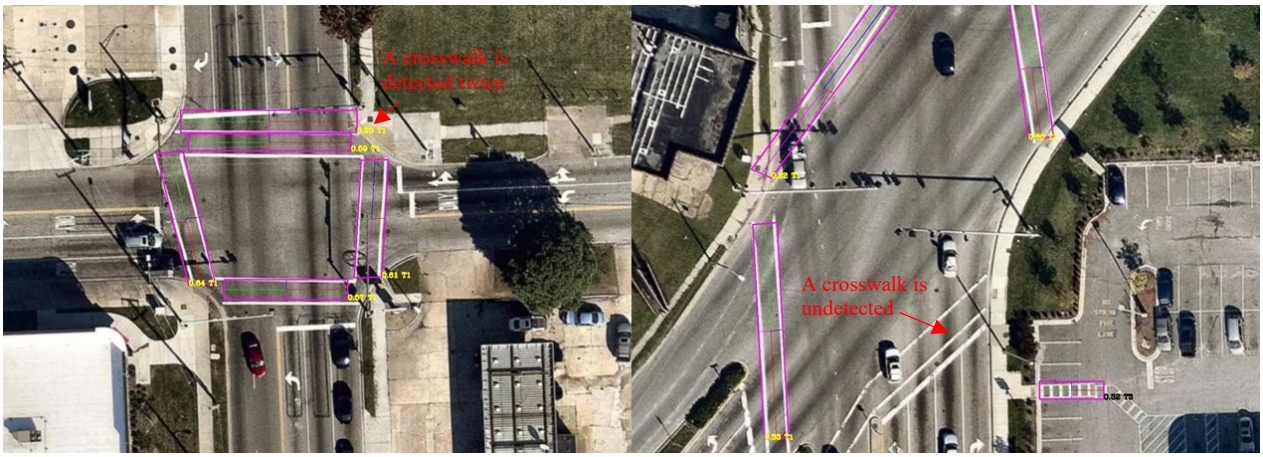


FIGURE 7 BBA Vectors network structure using airplane detection as an example *(15)*.

After developing the BBA Vectors model on the training set, the detection performance was evaluated on the testing set. Examples of correctly detected and incorrectly detected (e.g., misclassification, missing) crosswalks are presented in FIGURE 8 (refer to the APPENDIX for more detection results). Widely used metrics for object detection, *i.e.*, precision, recall, F-measure, and average precision were adopted to assess the detection performance on each crosswalk type as shown in TABLE 4. An overall average precision of 89% was achieved. It should be noted that T2 - Zebra Crosswalk class has a small number of instances (18) in the testing set, the detection results are perfect (with all metrics equal to 1).



(a) Correctly detected crosswalks



(b) Incorrectly detected crosswalks

FIGURE 8 Examples of correctly detected and incorrectly detected crosswalks. (Numbers indicate confidence levels)

TABLE 4 Crosswalk Detection Performance on the Testing Set

Crosswalk Type	Precision	Recall	F-measure	Average Precision
T1 - Transverse Crosswalk	0.61	0.88	0.72	0.89
T2 - Zebra Crosswalk	0.75	0.70	0.72	0.87
T3 - Ladder Crosswalk	0.62	0.89	0.73	0.92
Mean	0.66	0.82	0.72	0.89

(Note: Each metric is ranged between 0 to 1 and higher is better.)

Exploit Transfer Learning for Robust and Accurate Detection

Transfer learning was used to enhance the detection of lane-use arrows given its relatively poor performance as shown in TABLE 2. The framework of transfer learning is presented in FIGURE 9. A synthetic dataset was generated by image processing techniques. A Faster Region-based Convolutional Neural Networks (R-CNN) model was pre-trained on the synthetic dataset and then fine-turned on real data for detecting and classifying lane-use markings in the transfer learning process.

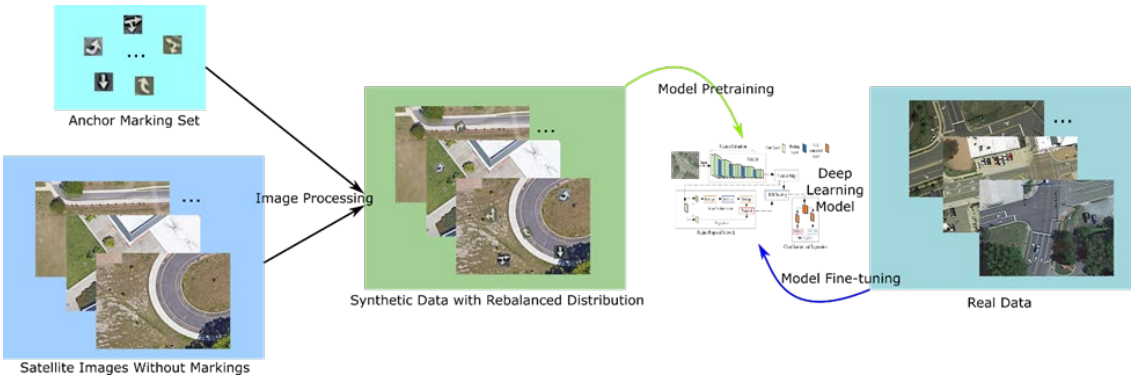


FIGURE 9 The framework of transfer learning.

A few images were randomly selected in the training set of real data and cropped ten traffic markings for each class. An adaptive image segmentation method OTSU *(17)* was then applied to each cropped marking image to obtain a clear anchor marking set without backgrounds.

The classes of traffic markings were not evenly distributed in the real dataset. For example, the left marking occurred more frequently than others, and the right & straight marking appeared fewer times than others. This imbalanced distribution might result in accuracy defects during the model training. This challenge was addressed by selecting one anchor marking from each class randomly and then adding these five anchor markings to one real satellite image that did not contain real traffic markings. Salt-and-pepper noises, presented as sparsely occurring white and black pixels, were randomly added to markings during the process. Finally, a synthetic and rebalanced dataset of 490 satellite images was generated, with five fake markings (one for each class) on each synthetic image.

As a result of transfer learning, the Faster R-CNN model developed for detecting lane-use arrows has further improved. The detection performance was evaluated ton the same testing set and the same metrics (*i.e.*, precision, recall, F-measure, and average precision) were used to evaluate the performance for comparison purposes. The results before and after transfer learning are presented in TABLE 2, TABLE 4 and TABLE 5, respectively. The performance of the Faster R-CNN model has been significantly improved after transfer learning in terms of all metrics used. The average precision is improved from 78% to 85% after the transfer learning and code optimization, compared with the detection performance of the last quarter.

TABLE 5 Lane-use Arrow Detection Performance on the Testing Set after Transfer Learning

Lane-use Arrows	Precision	Recall	F-measure	Average Precision
Left	0.94	0.57	0.71	0.92
Left & Straight	0.69	0.59	0.64	0.71
Straight	0.97	0.49	0.65	0.86
Right	0.91	0.58	0.71	0.89
Right & Straight	0.89	0.56	0.69	0.86
Mean	0.88	0.55	0.68	0.85

(Note: Each metric is ranged between 0 to 1 and higher is better.)

Marking Size Measurement

Methodology to compute the lengths and widths

The detection bounding box was used to measure the size of each marking as shown in FIGURE 10. Pixels were converted to feet. The actual physical sizes of markings were used to compute the conversion ratio R based on Eq. (1).

$$\boldsymbol{R} = \frac{\boldsymbol{Actual\ size\ in\ feet}}{\boldsymbol{Image\ size\ in\ pixels}} \tag{1}$$

As illustrated in FIGURE 11, as a result of marking detection, the coordinates for 4 corners of the bounding box were obtained, i.e., left bottom (LB), left top (LT), right bottom (RB) and right top (RT). The length and width of the detected marking can be calculated by corners' Euclidean distances. The actual length and width in feet can be calculated by Eq. (2) and Eq. (3).

$$\boldsymbol{length} = \mathbf{R} \times \frac{\sqrt{(\mathbf{x1}-\mathbf{x4})^2+(\mathbf{y1}-\mathbf{y4})^2}+\sqrt{(\mathbf{x2}-\mathbf{x3})^2+(\mathbf{y2}-\mathbf{y3})^2}}{\mathbf{2}} \tag{2}$$

$$\boldsymbol{width} = \mathbf{R} \times \frac{\sqrt{(\mathbf{x1}-\mathbf{x2})^2+(\mathbf{y1}-\mathbf{y2})^2}+\sqrt{(\mathbf{x3}-\mathbf{x4})^2+(\mathbf{y3}-\mathbf{y4})^2}}{\mathbf{2}} \tag{3}$$

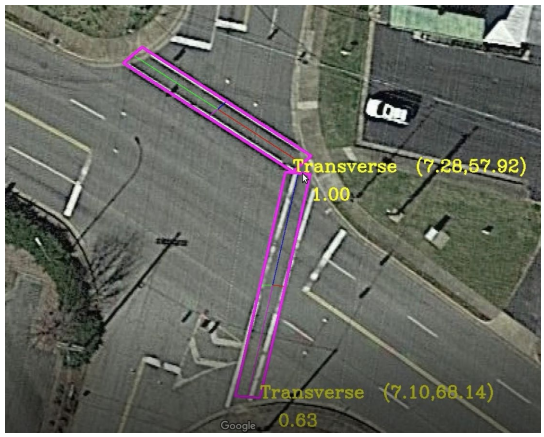


FIGURE 10 An example of crosswalk detection with bounding boxes. (Numbers in parentheses indicate widths and lengths of crosswalks in feet)

FIGURE 11 Bounding box with coordinates for computation illustration.

Evaluation using Intersection over Union (IoU)

Intersection over Union (IoU) *(18)* was used to indicate how trustworthy the measurements are. *Area of overlap* and area of union were obtained by comparing the detection bounding boxes with manually labeled bounding boxes. IoU can be computed by dividing *area of overlap* by *area of union* as in FIGURE 12.

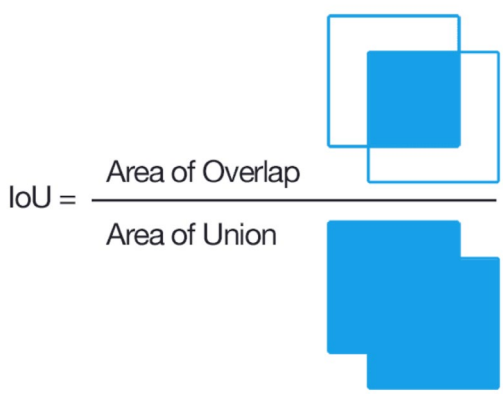


FIGURE 12 Illustration of Intersection over Union.

The Area of Overlap can be calculated by $Area\ of\ Overlap = (\min(x_{2,1}, x_{2,2}) - \max(x_{1,1}, x_{1,2})) \times (\min(y_{2,1}, y_{2,2}) - \max(y_{1,1}, y_{1,2}))$, where $(x_{1,1}, y_{1,1})$ and $(x_{2,1}, y_{2,1})$ are the top-left and bottom-right coordinates of the detection bounding box, and $(x_{1,2}\ y_{1,2})$ and $(x_{2,2}, y_{2,2})$ are the top-left and bottom-right coordinates of the labelled bounding box.

The Area of Union can be calculated by $Area\ of\ Union = (x_{2,1} - x_{1,1}) \times (y_{2,1} - y_{1,1}) + (x_{2,2} - x_{1,2}) \times (y_{2,2} - y_{1,2}) - Area\ of\ Overlap$.

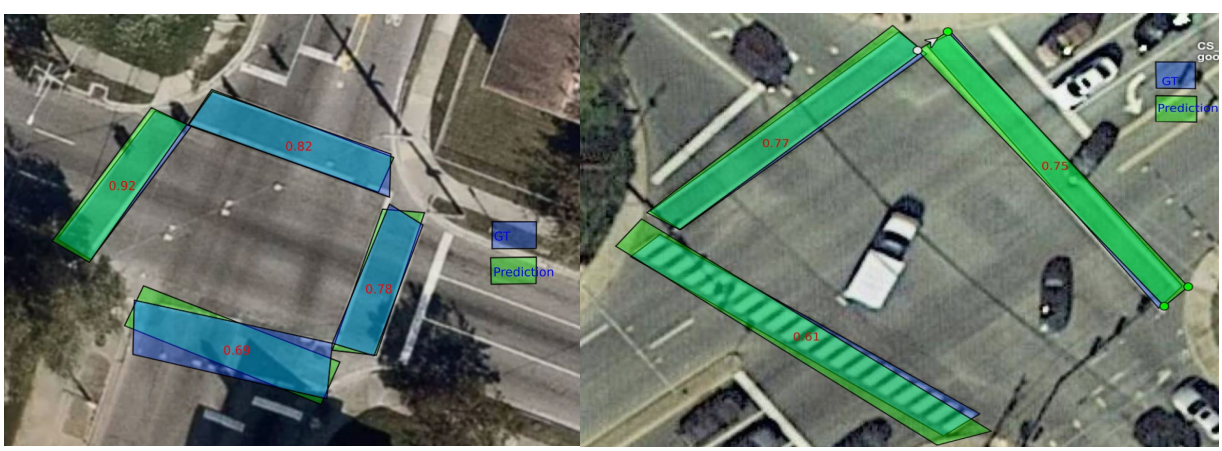
IoU ranges from 0 to 1, with 0 indicating no overlap and 1 indicating perfect overlap. IoUs of detection results on the testing set are shown in TABLE 6. The mean IoU has reached 0.75, which is considered as satisfactory.

TABLE 6 Intersection over Union (IoU) on the Testing Set

Crosswalk Type	**IoU**
T1-Transverse	0.75
T2-Zebra	0.76
T3-Ladder	0.75
Mean	**0.75**

Visualization examples with different IoUs

Examples of crosswalk detection with high IoUs and low IoUs are presented in FIGURE 13.



(a) Detection with high IoUs

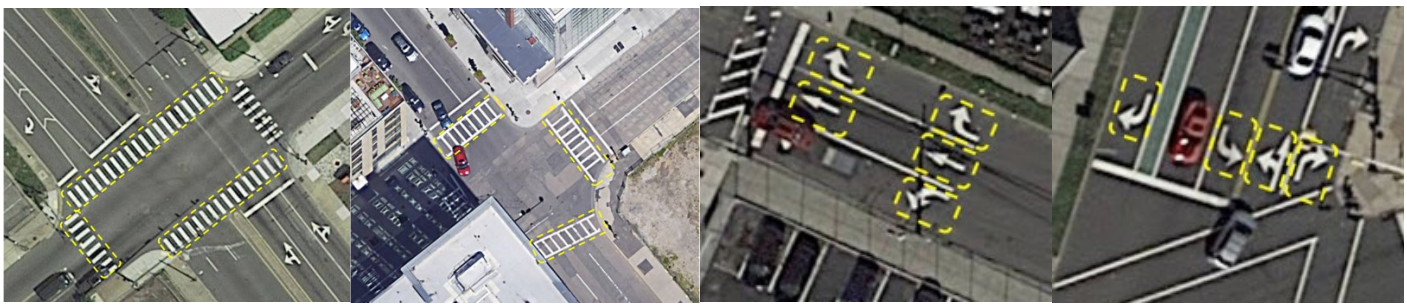
(b) Detection with low IoUs

FIGURE 13 Examples of crosswalk detections with high IoUs and low IoUs.

Assess the Degradation Conditions of Markings

Degradation conditions of markings were first manually annotated into two quality classes, i.e., low-quality and high-quality. If a marking (a lane-use arrow or crosswalk) is complete without any visible damage, it is classified as high-quality, otherwise it is classified as low-quality. Examples of low-quality and high-quality markings are presented in FIGURE 14.

(a) Low-quality



(b) High-quality

FIGURE 14 Examples of low-quality (a) and high-quality (b) degradation conditions.

A total of 6,396 lane-use arrows and 5,031 crosswalks were annotated by trained reviewers. TABLE 7 and TABLE 8 present the distributions of degradation conditions for lane-use arrows and crosswalks. The majority of markings (85.4% for lane-use arrows and 69.4% for crosswalks) are in the high-quality category.

TABLE 7 Degradation Conditions of Lane-use Arrows

Quality Type	Total No.	No. in Training Set	No. in Testing Set
Low-quality	1,154	923	231
High-quality	6,765	5,412	1,353
Sum	7,919	6,335	1,584

TABLE 8 Degradation Conditions of Crosswalks

Quality Type	Total No.	No. in Training Set	No. in Testing Set
Low-quality	1,327	1,061	266
High-quality	3,009	2,407	602
Sum	4,336	3,468	868

Kang *et al. (19)* used a convolutional neural network for image quality assessment. A deep convolutional neural network model VGG16 *(14)* was developed for condition assessment. VGG16 has great flexibility to learn the perception of human viewers on degradation conditions. The structure of VGG16 is presented in FIGURE 15.

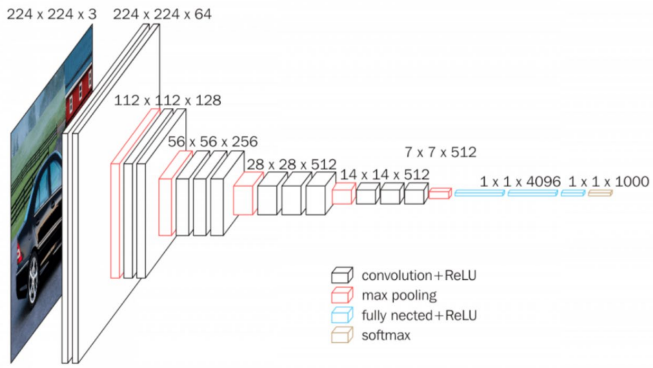
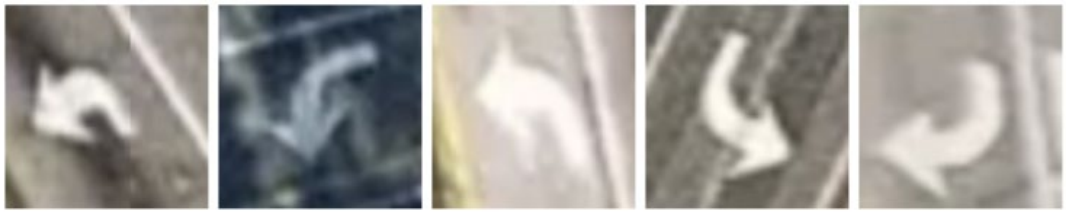


FIGURE 15 The VGG16 network structure for condition assessment.

After training the VGG16 model, the classification performance was evaluated on the testing sets of both lane-use arrows and crosswalks. Examples of correctly classified and incorrectly classified markings are presented in FIGURE 16. Accuracy (No. of corrected classified instances/total No. of instances) was used to evaluate the performance of conditions assessment as reported in TABLE 9. The overall accuracies for lane-use arrows and crosswalks have achieved 91% and 83%, respectively.

(a) Correctly classified lane-use arrows (Ground truth: High, High, High, Low, Low; Predict: High, High, High, Low, Low)



(b) Incorrectly classified lane-use arrows (Ground truth: High, High, High, Low, Low; Predict: Low, Low, Low, High, High)

(c) Correctly classified crosswalks (Ground truth: High, High, High, Low, Low; Predict: High, High, High, Low, Low)

(d) Incorrectly classified crosswalks (Ground truth: High, High, High, Low, Low; Predict: Low, Low, Low, High, High)

FIGURE 16 Examples of correctly classified and incorrectly classified markings based on degradation conditions.

TABLE 9 Condition Assessment Performance on the Testing Set

Quality Class	Low-quality (%)	High-quality (%)	Overall (%)
Lane-use arrow	80	94	91
Crosswalk	81	85	83

System Development

Back-end Development

The FastAPI[3] framework was chosen to build the back-end system. FastAPI is a modern, high-performance, and web-based framework for building Application Programing Interfaces (APIs) with Python 3.6+ based on standard Python type hints. The structure of the back-end system is shown in FIGURE 17. The back-end takes intersection images as the input. It comprises a computer vision module and an output module. The computer vision module detects and characterizes lane-use arrows and crosswalks and assesses their degradation conditions. The outputs include labeled intersection images and .csv files with all marking information.

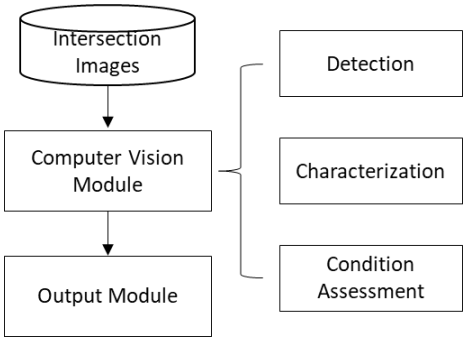


FIGURE 17 Back-end system structure and function diagram.

Front-end Development

For the front-end, the graphical user interface of the web-based system was developed so that users can view and interact with the system. JavaScript was used to create dynamic elements on static Hyper Text Markup Language (HTML) web pages. The Mapbox API was used to extract intersection aerial images from intersection coordinates inputted by users. The front-end workflow diagram is shown in FIGURE 18.

[3] https://github.com/tiangolo/fastapi

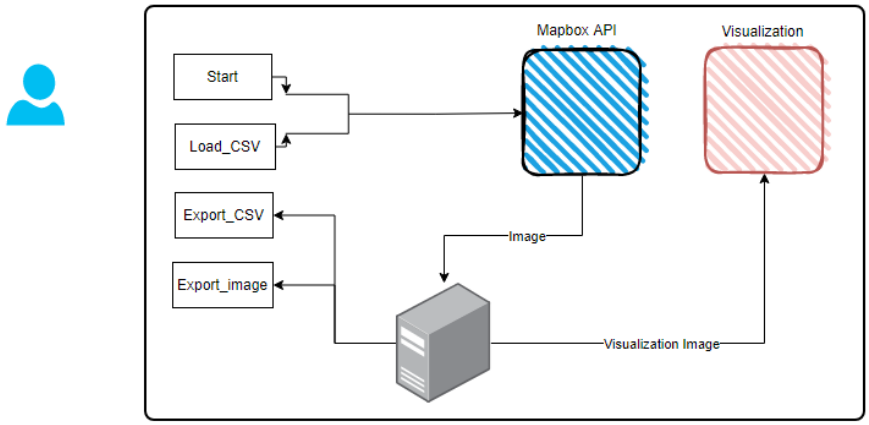


FIGURE 18 Front-end workflow diagram.

Input, Graphical User Interface, and Output

The input data contains intersection coordinate information and is tabulated in common .csv format. An example of the input data derived from LRS Road Intersections[4] is shown in TABLE 10. There are three columns including *Intersection_ID*, *Latitude*, and *Longitude*.

TABLE 10 Input Data Format

Intersection_ID	Latitude	Longitude
1269888	36.8201493	-75.99975
1085129	36.7805423	-76.141486
1045006	36.7744851	-76.133553
1037605	36.7802918	-76.142283
541180	36.8372126	-76.159457
541789	36.8785388	-76.141027
…	…	…

The graphical user interface of the system prototype is shown in FIGURE 19.

[4] LRS Road Intersections

FIGURE 19 Graphical user interface of the system prototype.

Intersection_ID	Latitude	Longitude	Marking_ID	Type	SubType	Location	Quality	Length	Width
541355	36.81321	-76.125	1	Crosswalk	Zebra	[839, 354, 785, 385, 445, 69, 499, 37]	0.77	75.4	10.4
541355	36.81321	-76.125	2	Crosswalk	Ladder	[839, 354, 785, 385, 445, 69, 499, 37]	0.75	75.4	10.4
541355	36.81321	-76.125	3	Crosswalk	Ladder	[491, 933, 436, 966, 99, 673, 153, 640]	0.99	72.6	10.6
541355	36.81321	-76.125	4	Crosswalk	Ladder	[491, 46, 201, 587, 138, 566, 427, 25]	0.72	102.7	10.8
541355	36.81321	-76.125	5	Crosswalk	Ladder	[828, 392, 606, 967, 546, 952, 769, 376]	1	103.3	10
541355	36.81321	-76.125	6	Arrow	Left	[183, 67, 183, 124, 222, 124, 222, 67]	0.98		
541355	36.81321	-76.125	9	Arrow	Left	[164, 103, 164, 151, 206, 151, 206, 103]	0.99		
541355	36.81321	-76.125	10	Arrow	Straight	[788, 1004, 788, 1050, 845, 1050, 845, 1004]	0.99		
541355	36.81321	-76.125	11	Arrow	Straight	[227, 40, 227, 84, 271, 84, 271, 40]	0.99		
541355	36.81321	-76.125	13	Arrow	Right	[744, 1056, 744, 1098, 797, 1098, 797, 1056]	0.99		
1269888	36.82015	-75.9998	14	Crosswalk	Transverse	[1127, 557, 1071, 560, 1022, 268, 1079, 264]	0.95	48.1	9.5
1269888	36.82015	-75.9998	15	Crosswalk	Transverse	[630, 612, 578, 624, 429, 263, 481, 251]	1	63.3	8.9
1269888	36.82015	-75.9998	16	Crosswalk	Transverse	[1003, 234, 993, 285, 476, 252, 487, 200]	0.97	84	8.8
1269888	36.82015	-75.9998	17	Crosswalk	Transverse	[1096, 612, 643, 676, 629, 630, 1082, 566]	0.83	76.6	7.8

FIGURE 20 Sample of an exported .csv file.

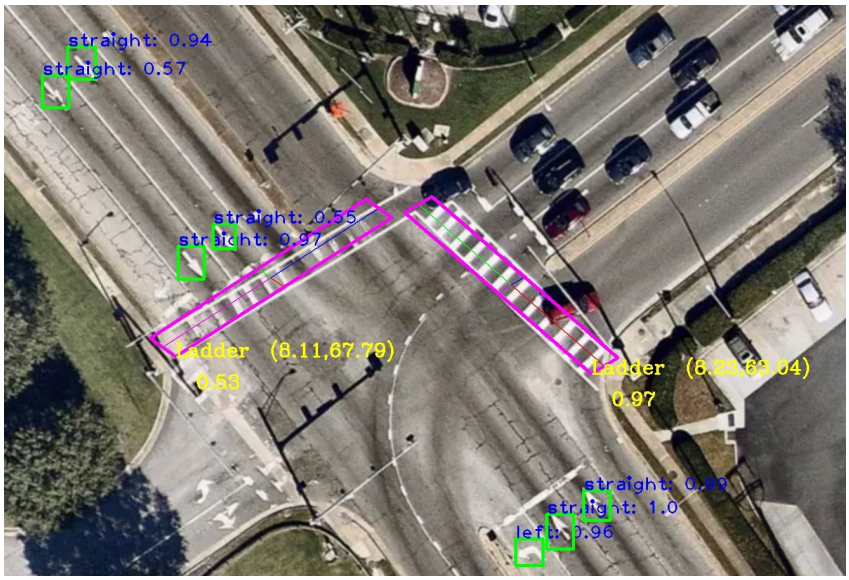


FIGURE 21 Sample of an exported .jpg file. (Numbers outside of parentheses are quality scores, numbers within parentheses are widths and lengths of crosswalks)

The field description of the exported .csv data file is presented in TABLE 11.

TABLE 11 Field Description of the Exported .csv Data

Field	Description	Example
Intersection_ID	ID of intersections from the input file	541465
Latitude	Coordinate that specifies the north–south position of an intersection	36.6830800700893
Longitude	Coordinate that specifies the east–west position of an intersection	76.0231042794389
Marking_ID	ID of markings started from 1	1
Type	Marking types such as crosswalks or lane-use arrows	Crosswalk
SubType	Crosswalks have three subtypes, i.e., transverse, zebra, and ladder; lane-ues arrows have five subtypes, i.e., left, right, left & straight, right & straight, and straight	Ladder
Location	Coordinates of four corner points of the detection bounding box. The Y-pixel coordinate increases from top to bottom and the X-pixel coordinate increases from left to right.	[790, 282, 438, 313, 425, 276, 777, 245]
Quality	Describe marking degradation condtion, ranging from 0 (lowest quality) to 1 (highest quality)	0.89

Length	The length of a crosswalk in feet	59.1
Width	The width of a crosswalk in feet	6.4

User Guidance

The graphical user interface is illustrated in FIGURE 19. A quick guide to use the system is described as follows.

- Step 1. Click **Input** to upload the prepared input data that contains intersection coordinates.
- Step 2. Click **Start** to start image extraction and processing all intersections contained in the input file until **End**.
- Step 3. Click **End** to stop the data collection program.
- Step 4. Click **Output** by selecting **CSV** to save all marking information (including locations, types, quality scores, etc.) as a .csv data file (see FIGURE 20 as an example). The .csv file is named in the format of the date as "*month_day_year_overall_csv.csv*".
- Step 5 (optional). Click **Output** by selecting **Image** to save all labelled intersection images as .jpg files for further examination (see FIGURE 21 as an example). The .jpg file is named by intersection ID.

PLANS FOR IMPLEMENTATION

The developed system is intended to innovate state DOTs' data collection efforts for safety improvement programs and infrastructure data inventories. The research team will comply with the guidance and requirements of the IDEA program and actively seek the opportunities to transfer the developed system into practices.

The research team will collaborate with the Virginia Department of Transportation (VDOT) to conduct a pilot test of the developed system on its public roadway network. VDOT will provide statewide intersection GIS data and other relevant data for large-scale implementation and performance evaluation of the developed system. VDOT will also assist in incorporating collected data products into its existing roadway inventory database. With the feedback and experience learned from the pilot test, the research team will consistently improve the system to meet the needs of transportation agencies.

The developed system will be deployed as a web-based application so that it does not require powerful client computers and any users with internet connections can easily access it. The research team will consult VDOT and Caltrans representatives and some others of interest to learn the best service plan from their perspectives, considering the maintenance, cost, training, etc. Overall, the research team inclines to promote the use of the system through the grant of licenses and keep maintaining it. Certainly, using contractual service to help agency develop the datasets is also possible. Maintaining the web

software system by agencies will be challenging as it typically requires additional resources (e.g., dedicated staff) to oversee and/or maintain the system. This may not be a rational plan for agencies with limited resources. The research team will try to provide different options to facilitate agencies using the system. Necessarily incurred costs will be supported by the users to cover the operational and maintenance expenses. The cost will depend on how much the requested efforts from the research team, for example, just maintaining the system or requiring the team to develop the final data product. The exact format of collaboration and associated cost will be based on the mutual agreement between the research team and the users.

CONCLUSION

This project develops an automated system that utilizes advanced computer vision models to detect and characterize intersection markings and assess their condition. A summary of the investigation results are as follows:

- A Faster RCNN model was developed to detect lane-use arrows. The average precision has achieved 85% on the testing set.
- Developed a BBAVectors model that can capture rotated objects to detect crosswalks and achieved an average precision of 89%.
- Marking images were synthesized from different environment settings and the synthesized data was used in a transfer learning process to pre-train computer vision models, leading to an enhanced model performance.
- Marking sizes were measured by calibrating the detection bounding boxes. Intersection over Union (IoU) was used to indicate how trustworthy the measurements were. An IoU of 0.75 was achieved, which is considered satisfactory.
- A VGG16 model was developed to assess the degradation conditions of markings. The overall accuracies for lane-use arrows and crosswalks achieved 91% and 83%, respectively.

From the investigation, it is found that emerging artificial intelligence techniques (e.g., deep learning, transfer learning) could deliver satisfactory data products in terms of detection, characterization, and condition assessment of intersection markings. The model performance could be further enhanced when additional data are used for model development.

The seamless integration of spatial analytics and advanced computer vision techniques makes the system truly cost-effective, scalable, and computationally efficient. The system harnesses emerging artificial intelligence techniques such as multi-task deep learning and transfer learning to enhance its robustness, accuracy, and computational efficiency. The system is very accessible to users of different technical skills through its graphical user interface.

Existing intersection marking data are generally collected either by field investigation or computer-aided manual extraction from aerial images, street views, and/or video logs. These approaches are cost prohibitive and only feasible for very limited data collection needs. In addition, their inherently subjective nature requires extensive trainings to reduce human errors. The system offers distinct advantages to innovate current practices: (a) extremely low cost, (b) extraordinary scalability, (c) timeliness and consistency, and (d) objective and high-degree reproducibility. The system can automate statewide intersection marking data collection at almost zero cost and with machine-based objective measurements. It can enhance timeliness and consistency of roadway inventory data by rapidly processing latest aerial image data periodically. It eliminates the exposure of surveyors to hazards in field data collection. Unlike manual data collection, the system also provides objective measurements and a high-degree reproducibility of collected data.

The system can generate data elements highly expected by the state Departments of Transportation (DOTs) to support the Model Inventory of Roadway Elements (MIRE) program and to advance Highway Safety Improvement Programs (HSIP). Current data collection practices require DOTs to invest millions of dollars in contracting very time-consuming data collection services each year. By economically providing large-scale intersection marking data, this system will enable state DOTs to empower analytic methods for data-driven safety management. The system can also assess the degradation condition of identified markings, and thus timely assist maintenance prioritization for reinforcing intersection safety.

INVESTIGATORS' PROFILES

Kun Xie, Ph.D.: Dr. Xie is currently a tenure-track Assistant Professor in the Department of Civil and Environmental Engineering at Old Dominion University (ODU). He completed his PhD in Transportation Planning and Engineering from New York University (NYU). His research concentrates on the use of data-driven approaches and emerging technologies to enhance the safety, efficiency, and resiliency of transportation systems. He has successfully helped secure external funding from National Science Foundation (NSF), USDOT, VDOT, and industry partners. In a research project accomplished recently, he utilized computer vision techniques to automatically extract rich traffic information from large-scale video data and then leveraged the traffic information to empower road safety management. Knowledge and experience gained from this project benefit every aspect in developing the system. He has published over 100 refereed papers in scholarly journals and conference proceedings. He is recognized by prestigious awards such as IEEE ITSS Best Dissertation Award, CUTC Milton Pikarsky Memorial Award and Transportation Research Board (TRB) Best Paper Award for his research outcomes. He has chaired a special session—Big Data and Emerging Technologies for Traffic Safety Improvement at the IEEE ITSC 2019.

Hong Yang, Ph.D.: Dr. Yang is a tenured Associate Professor in the Department of Electrical and Computer Engineering at ODU. Prior to join ODU, he was a postdoctoral researcher at the Center of Urban Science and Progress and the Department of Civil and Urban Engineering at NYU. His research interests span the development of advanced models and data analytics for transportation safety assessment, modeling and simulation of large-scale complex transportation systems, advanced technology and sensing applications for ITS, urban informatics and data science for smart mobility, and machine learning and artificial intelligence for traffic operations. He has been Principal Investigator, Co-Principal Investigator, and lead researcher of several research projects funded by USDOT/FHWA, VDOT, NJDOT, and others. In his career, he has authored or co-authored more than 100 refereed articles in prestigious academic journals and international conference proceedings. His research work on urban freight safety has received the 2015 TRB Best Paper Award.

Hongkai Yu, Ph.D.: Dr. Yu is an Assistant Professor of Electrical Engineering and Computer Science at the Cleveland State University (CSU). He obtained his Ph.D. degree in Computer Science and Engineering from the University of South Carolina in 2018. He is the Director of the Cleveland Vision & AI Lab, with research focused on computer vision, deep learning, and artificial intelligence applications in transportation, autonomous driving, and remote sensing. He has published 32 papers on prestigious conferences and journals, such as CVPR, AAAI, TRB Annual Meeting, and IEEE Transactions. He has

been invited as the Guest Associate Editor for IEEE GRSL journal in 2018 and the chair for the 2020 International Workshop on Ubiquitous Mobile Service for Intelligent Transportation (USIT-20). His research has been supported by Air Force Research Lab, FHWA, NVIDIA, etc.

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APPENDIX I: RESEARCH RESULTS

SIDEBAR INFO

Program Steering Committee: NCHRP IDEA Program Committee
Month and Year: January 2023
Title: An Automated System for Large-scale Intersection Marking Data Collection and Condition Assessment
Project Number: 225
Start Date: January 1, 2021
Completion Date: December 31, 2022
Product Category: New or improved tool or equipment
Principal Investigator: Kun Xie, Assistant Professor
E-Mail: kxie@odu.edu
Phone: 757-683-4304

TITLE

Collecting Intersection Marking Data Automatically

SUBHEAD

Developed an artificial intelligence-powered system to automatically detect and characterize intersection markings and to assess their degradation conditions

WHAT WAS THE NEED?

Intersection markings play a vital role in providing road users with guidance and information. The conditions of intersection markings will be gradually degrading due to vehicular traffic, rain, and/or snowplowing. Degraded markings can confuse drivers, leading to increased risk of traffic crashes. Timely obtaining high-quality information of intersection markings lays a foundation for making informed decisions in safety management and maintenance prioritization. However, current labor-intensive and high-cost data collection practices make it very challenging to gather intersection data on a large scale. Therefore, it immediately requires a cost-effective tool that can accurately and efficiently collect statewide intersection marking data.

WHAT WAS OUR GOAL?

Our goal is to develop an automated system for large-scale intersection marking data collection and condition assessment by utilizing emerging AI technologies and open-source data.

WHAT DID WE DO?

Our system economically utilizes roadway GIS data and aerial images as inputs, which are commonly available from state DOTs or open sources. The system focuses on two types of markings at intersections – lane-use arrows and crosswalks, while it has the flexibility to be extended to cover other road markings as well. We first developed a data acquisition module to automatically retrieve intersection locations from roadway GIS data in Virginia and capture corresponding aerial images on a large scale. Over 3,000 intersection images have been captured and manually annotated. By utilizing the extracted intersection image data, we then developed a computer vision module for detection, characterization, and condition assessment of intersection markings. We harnessed emerging artificial intelligence techniques such as

transfer learning and multi-task deep learning to enhance the robustness, accuracy, and computational efficiency of the system. Finally, we integrated the data acquisition and computer vision modules developed and built a graphical user interface (GUI) for the system. We deployed the system as a web-based application so that it does not require powerful client computers and any users with internet connections can easily access it.

WHAT WAS THE OUTCOME?

Our system was able to detect and classify lane-use arrows at an 85% average precision and crosswalks at an 89% average precision. It also could reliably measure the marking sizes and assess the degradation conditions of lane-use arrows at a 91% overall accuracy and crosswalks at an 83% overall accuracy. We found that emerging artificial intelligence techniques (e.g., deep learning, transfer learning) could deliver satisfactory data products in terms of detection, characterization, and condition assessment of intersection markings. The system performance can be further enhanced when additional annotated data are available in the future.

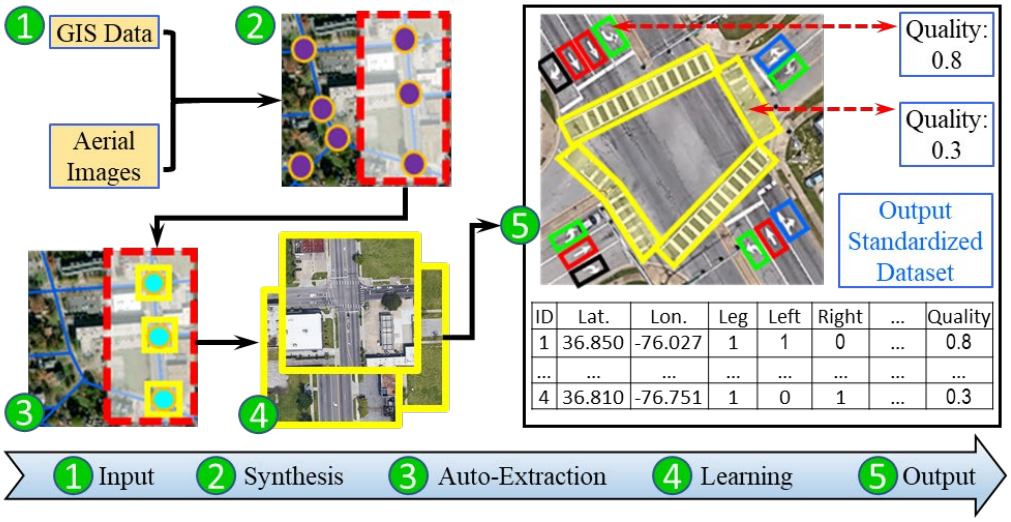
WHAT IS THE BENEFIT?

Our system can fully automate the processes of marking data collection and condition assessment on a large scale with almost zero cost and short processing time (e.g., in a preliminary test, the processing time per intersection is less than 2 seconds). The system can help states improve their inventory databases to accommodate data requirements legislated in the MAP-21 and the FAST Acts. The large-scale data produced through the developed system can greatly benefit transportation agencies in several key aspects such as intersection safety management, infrastructure maintenance prioritization, and transportation planning modeling.

LEARN MORE

Link will be added when the report is published.

IMAGES

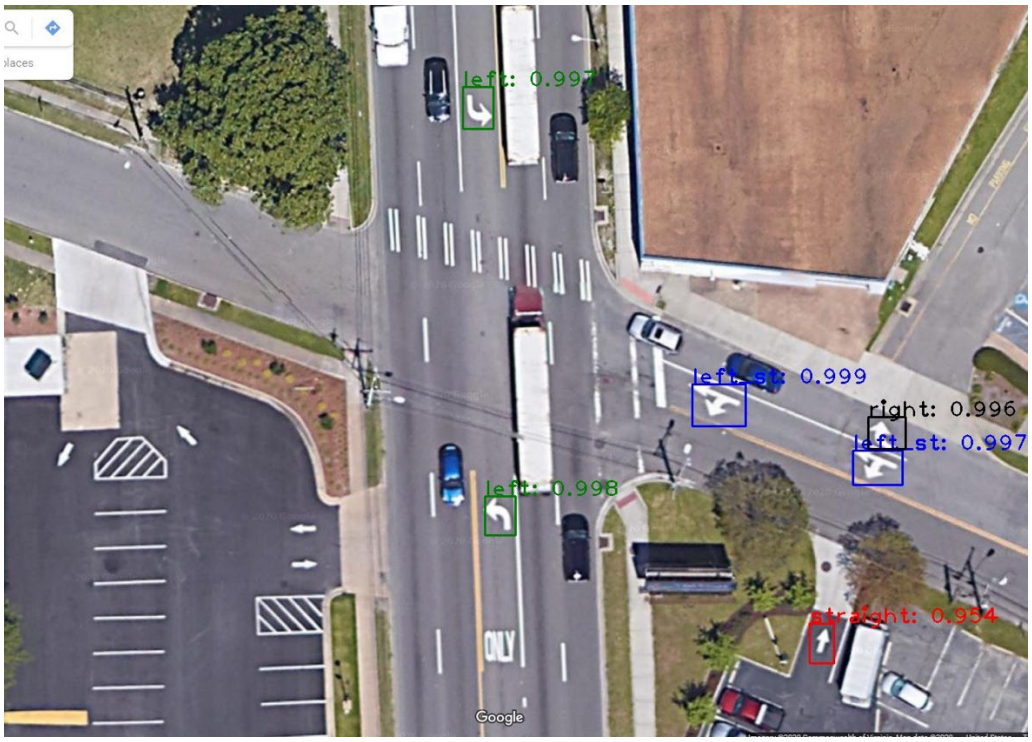


Conceptual illustration of the automated data collection system

APPENDIX II: EXAMPLES OF MARKING DETECTIONS RESULTS

Lane-use Arrow Detection

Corrected Detections

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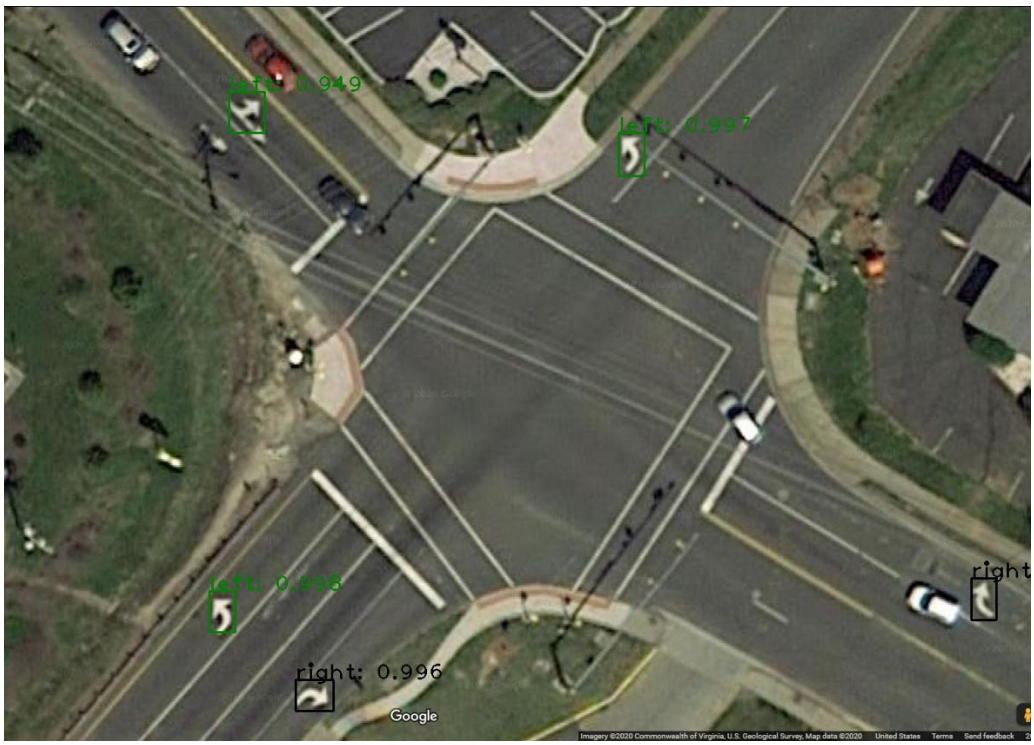
right: 0.999
right: 0.997
left: 0.991
Google


left: 0.997
left: 0.997
left: 0.991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Google


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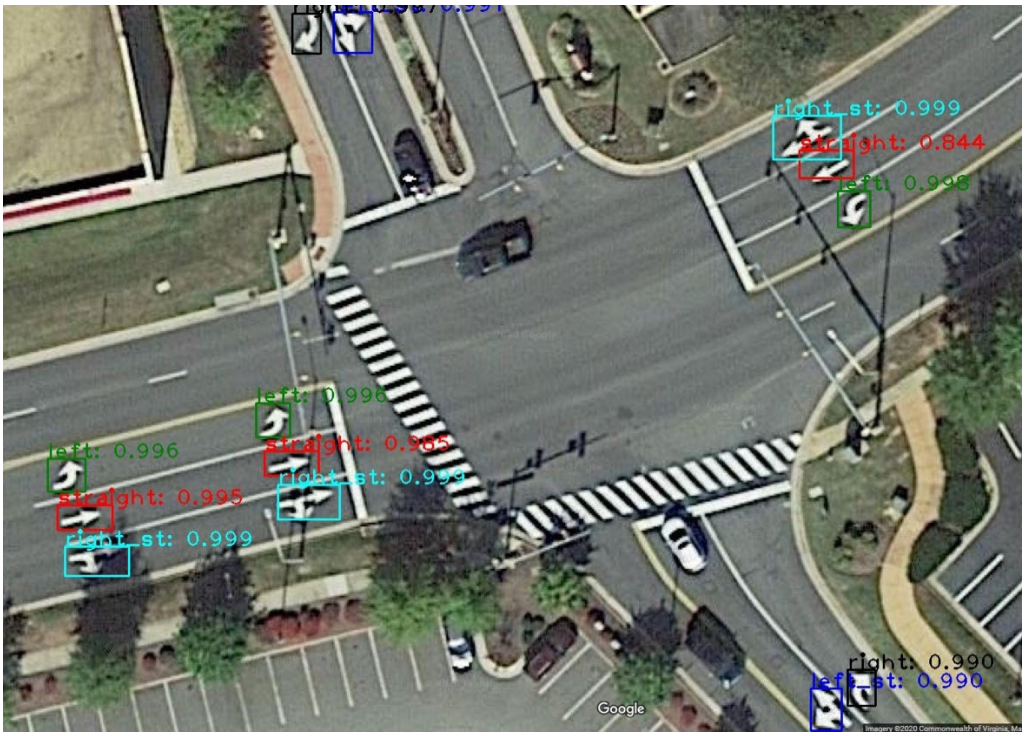
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left: 0.998
left: 0.996
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left: 0.996
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right_st: 0.999
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left_st: 0.990
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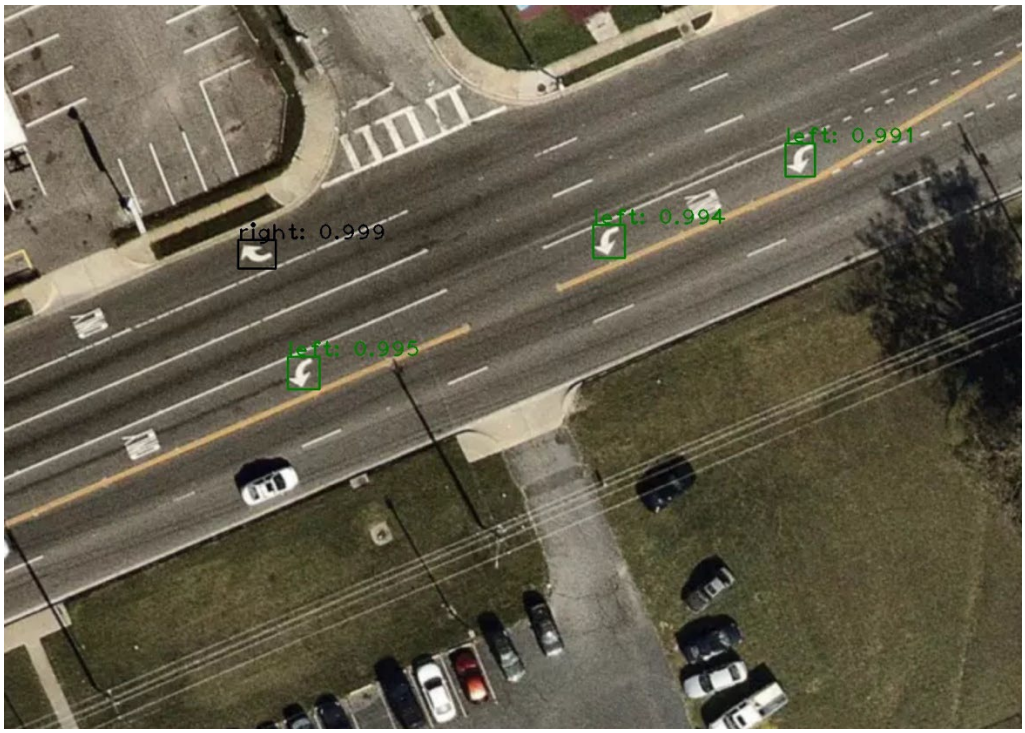
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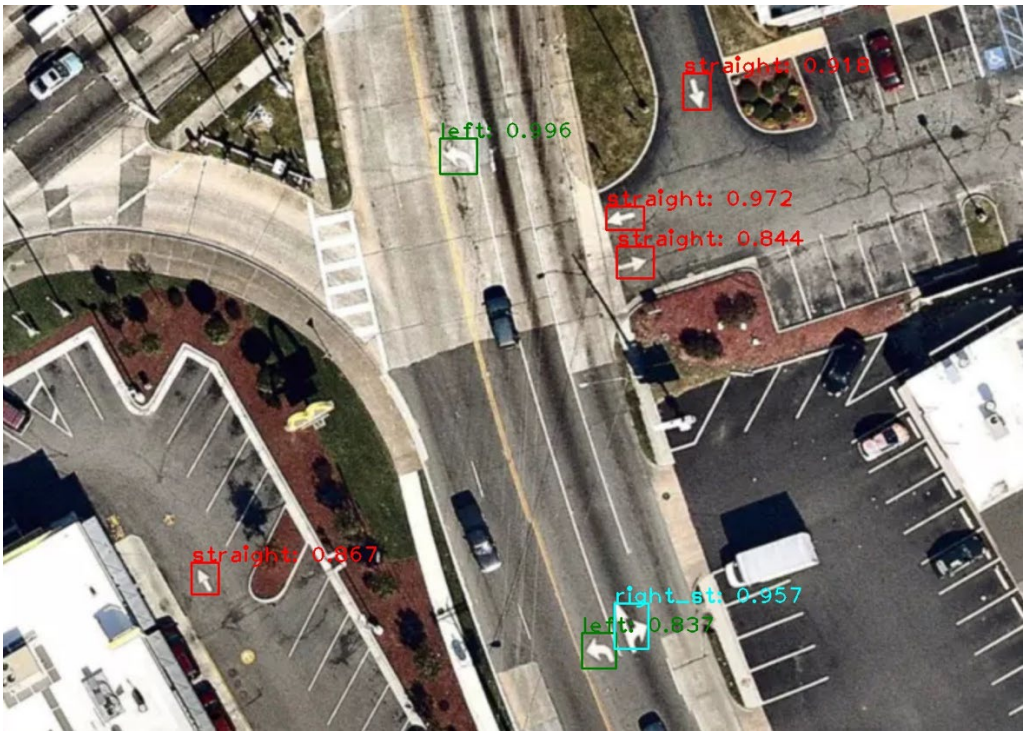
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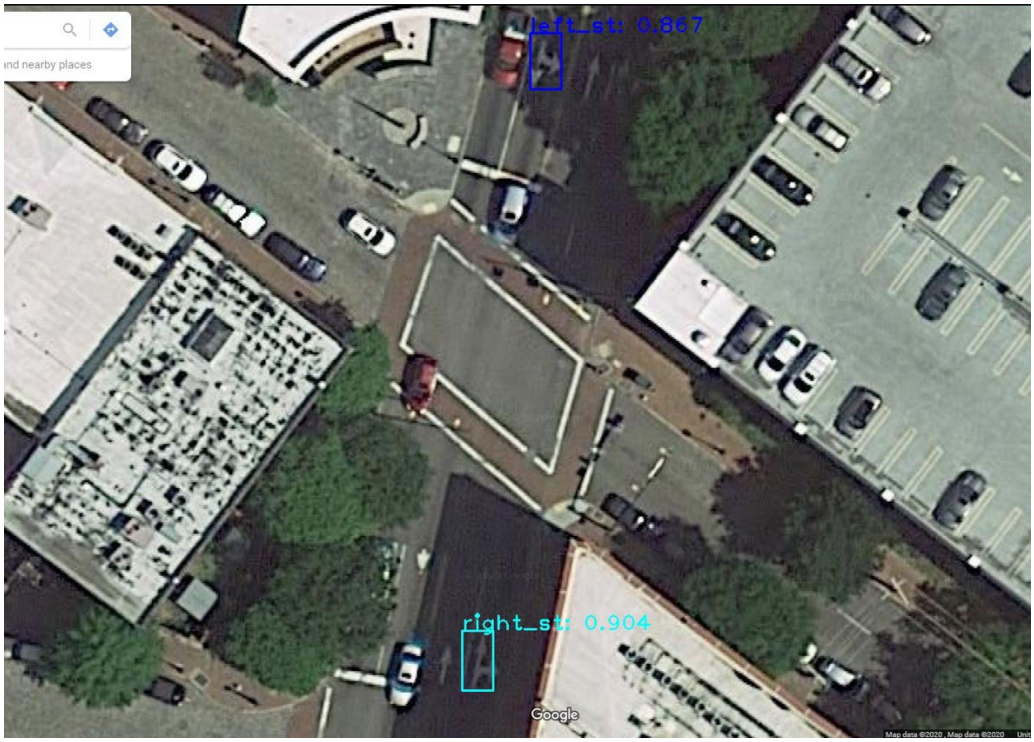
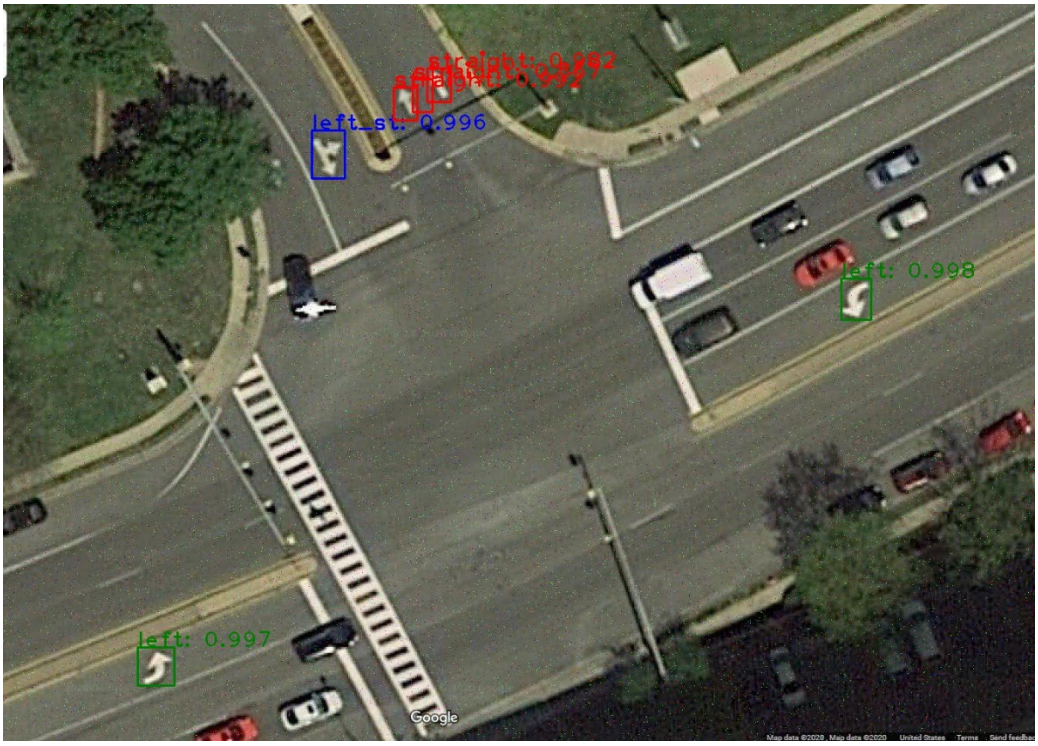
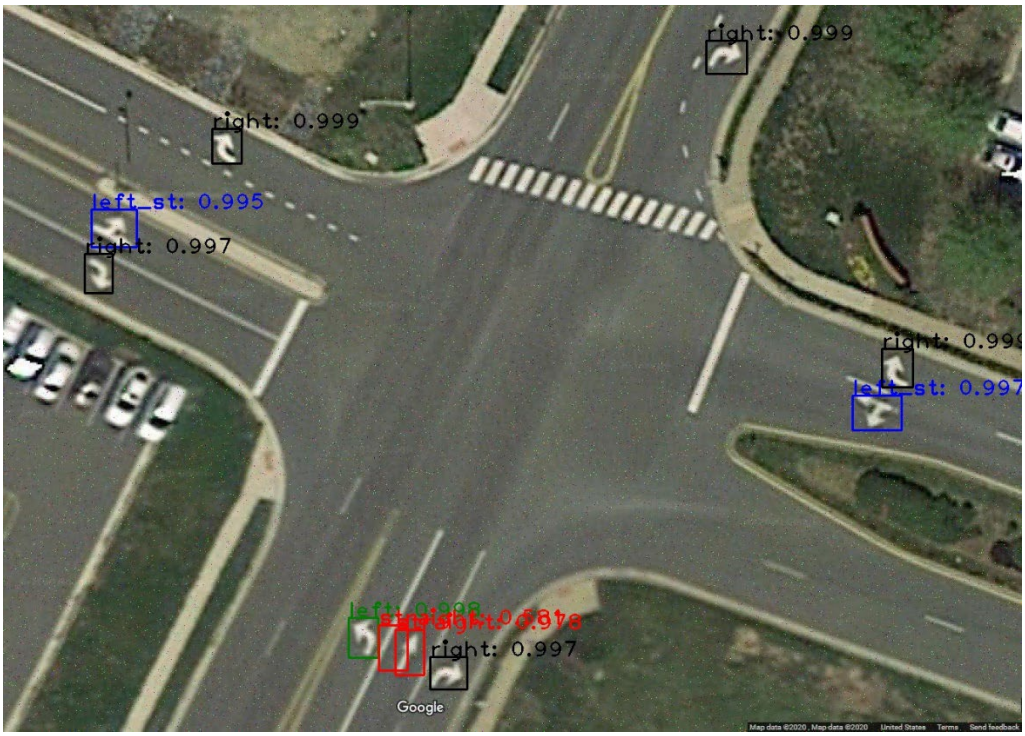
straight: 0.972
straight: 0.844
straight: 0.867
right_st: 0.957
left: 0.837

Incorrected Detections






left: 0.998
right:
Google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left_st: 0.995
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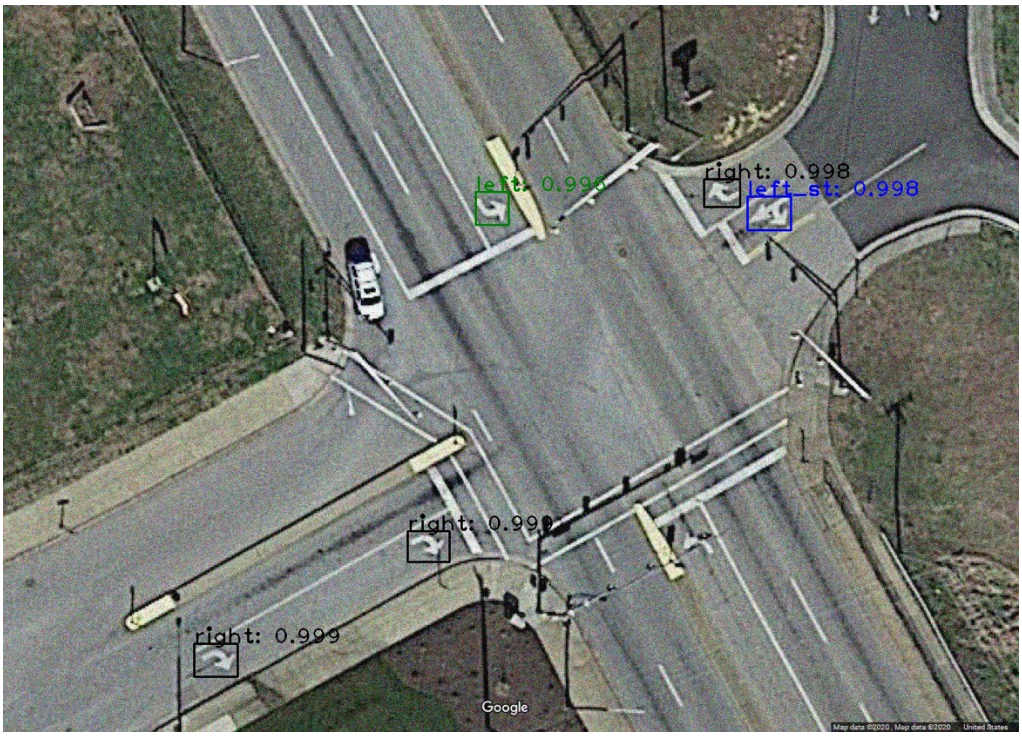
right: 0.997
Google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right: 0.999
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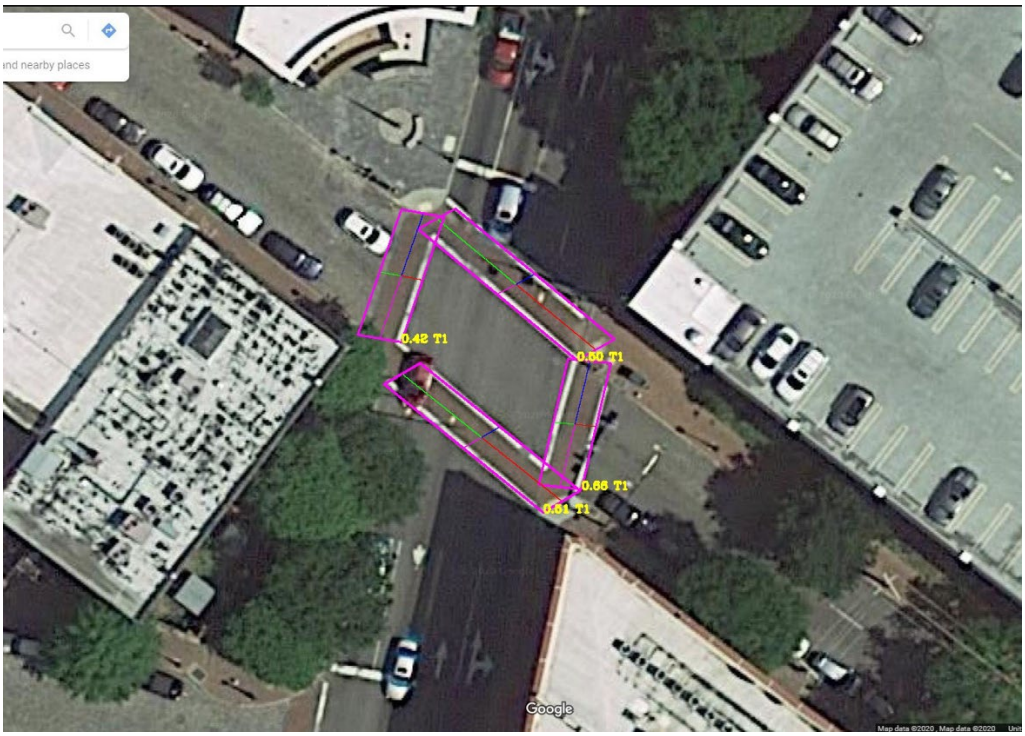
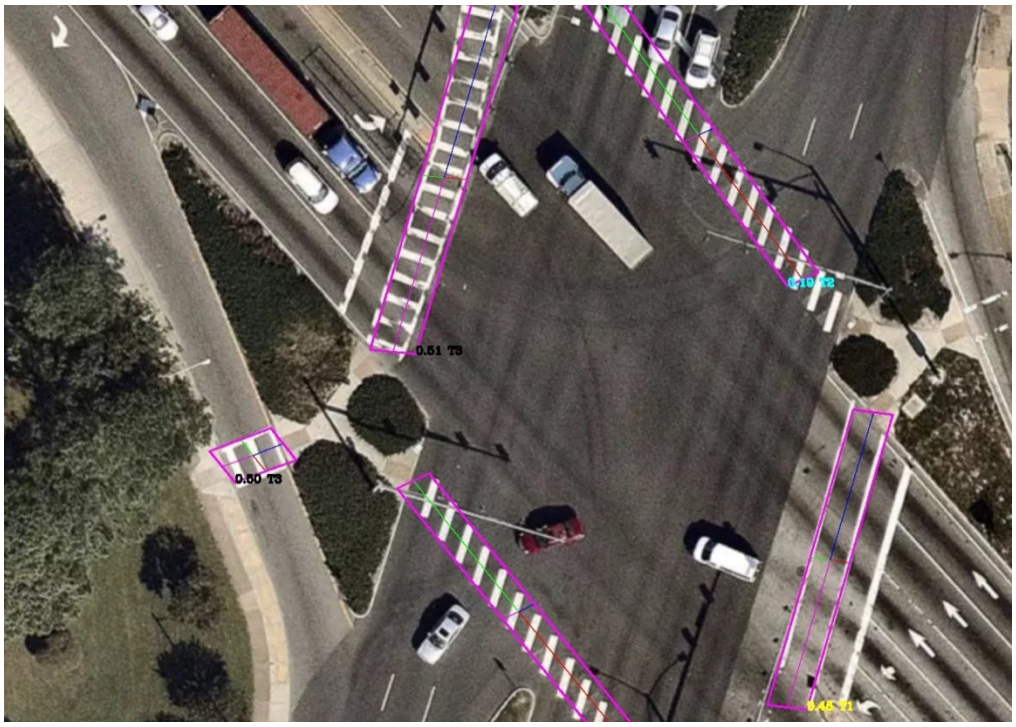
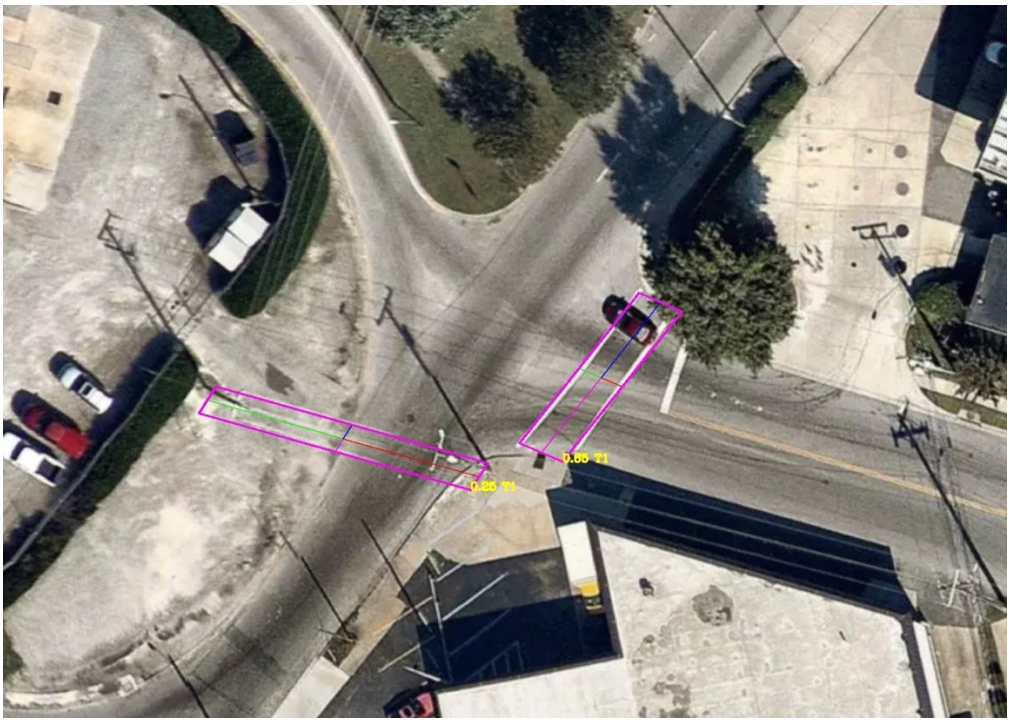
Google

Crosswalk Detection

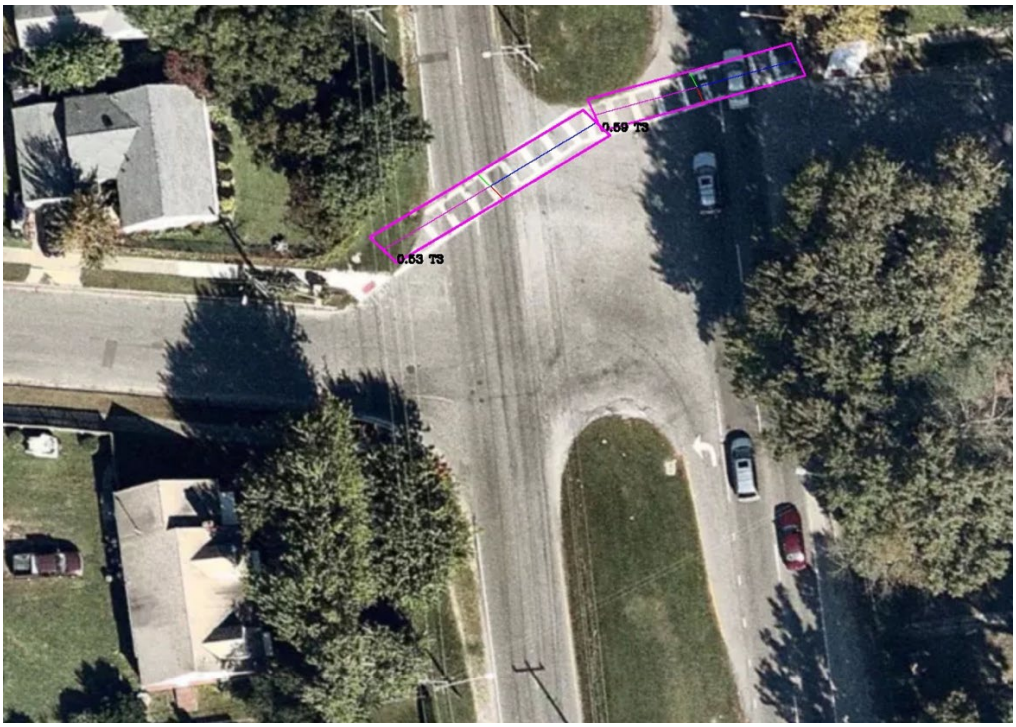
Corrected Detections



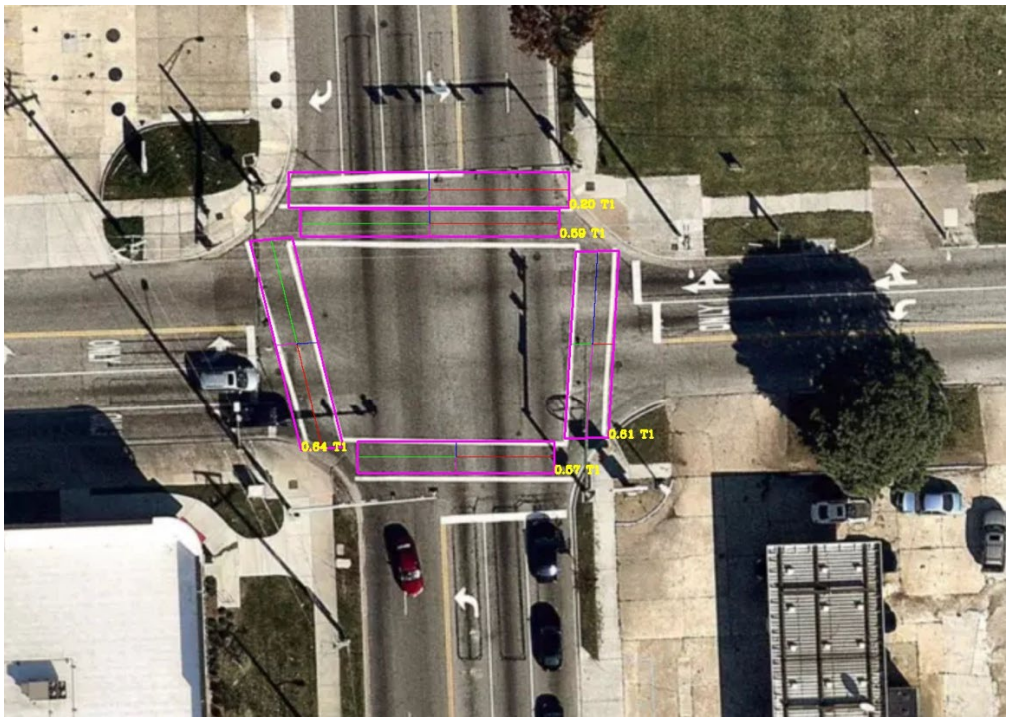


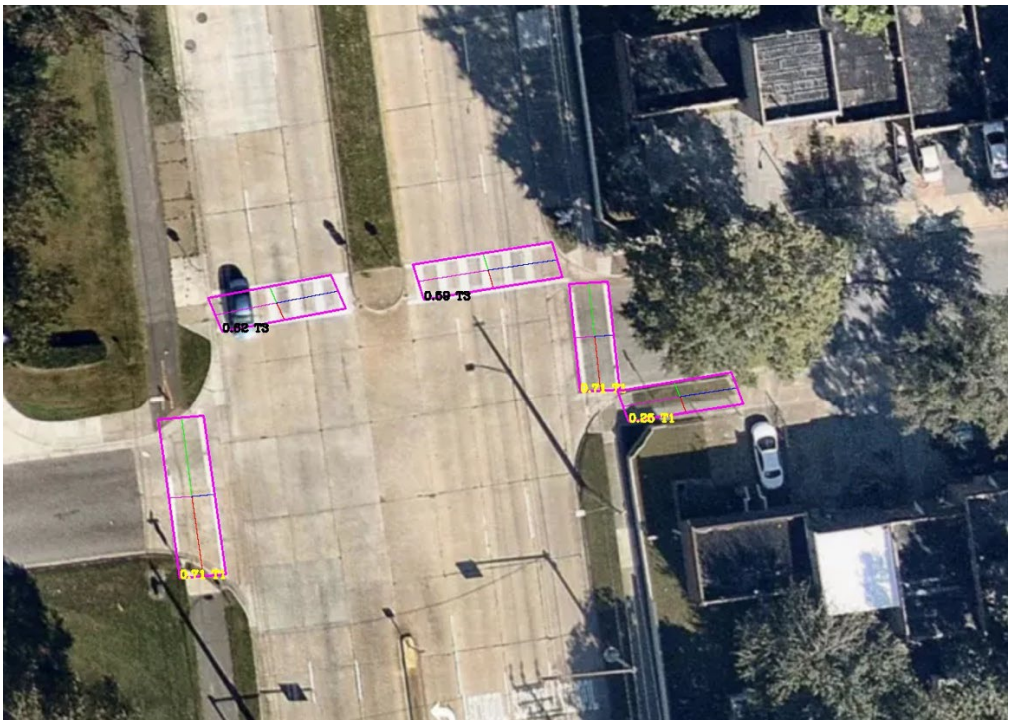

0.66 T1
0.66 T1

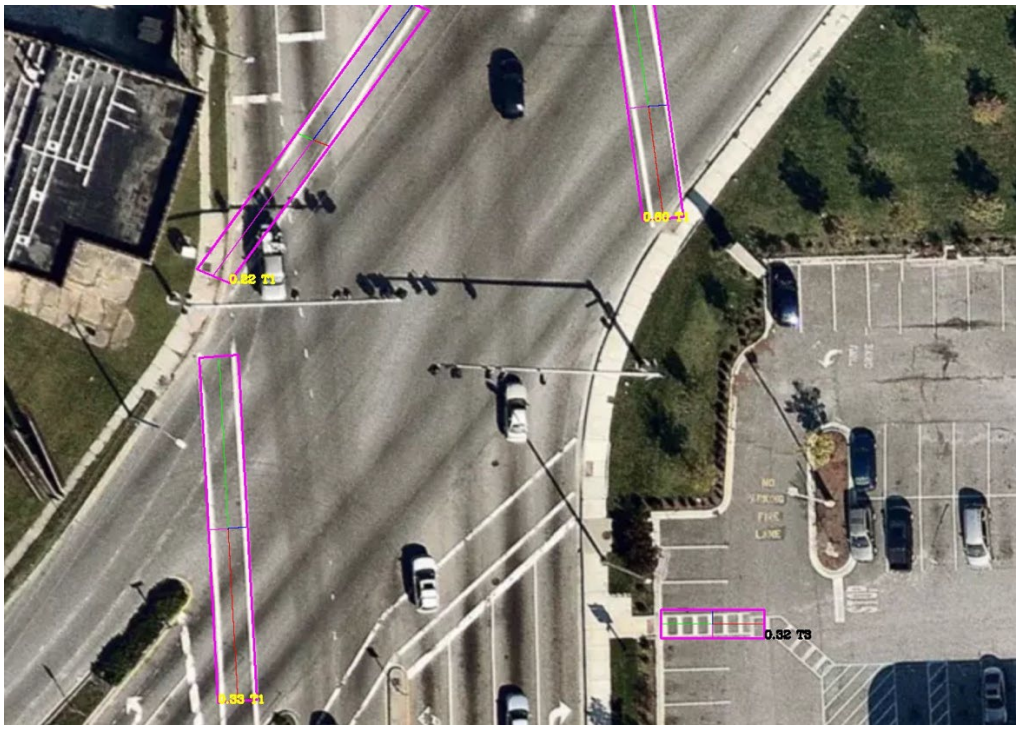

0.66 T1



Incorrected Detections




0.52 T3
0.59 T3
0.26 T1


0.62 T1
0.66 T1
0.52 T3
0.53 T1


0.49 T2


0.37 T3
0.57 T3