

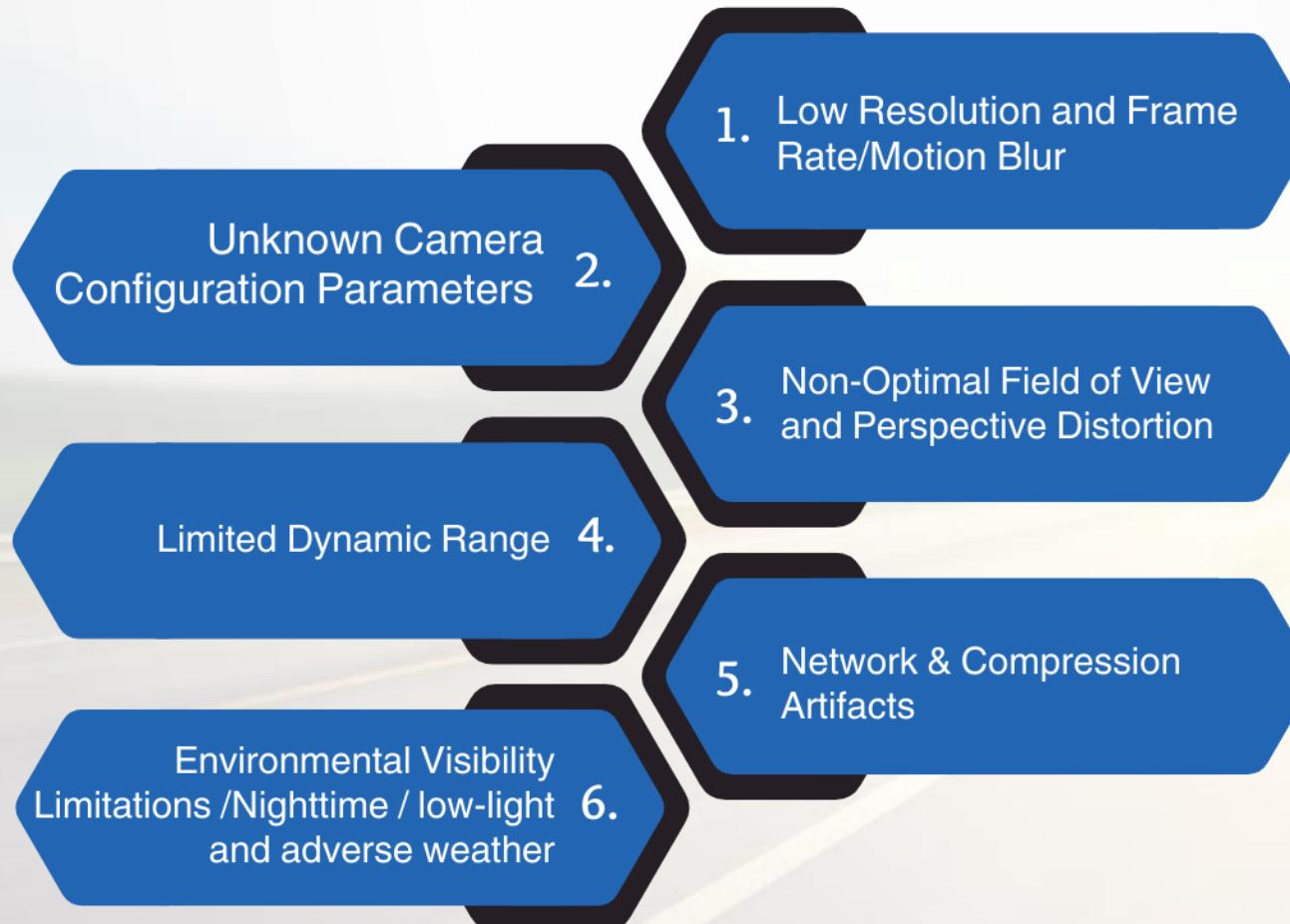


Transforming Traffic Surveillance Cameras into Intelligent Sensors: A Machine-Learning Approach for Cost-Effective, High-Quality Monitoring

*Presented by: Tara Diba
2025 Modeling Mobility Conference
September 15, 2025*

- Motivation and Scope
- Methodology Overview
- Automated Data Acquisition
- Algorithm
- Results
- Conclusions and Future Work

Physical and Environmental Constraints of Camera Systems

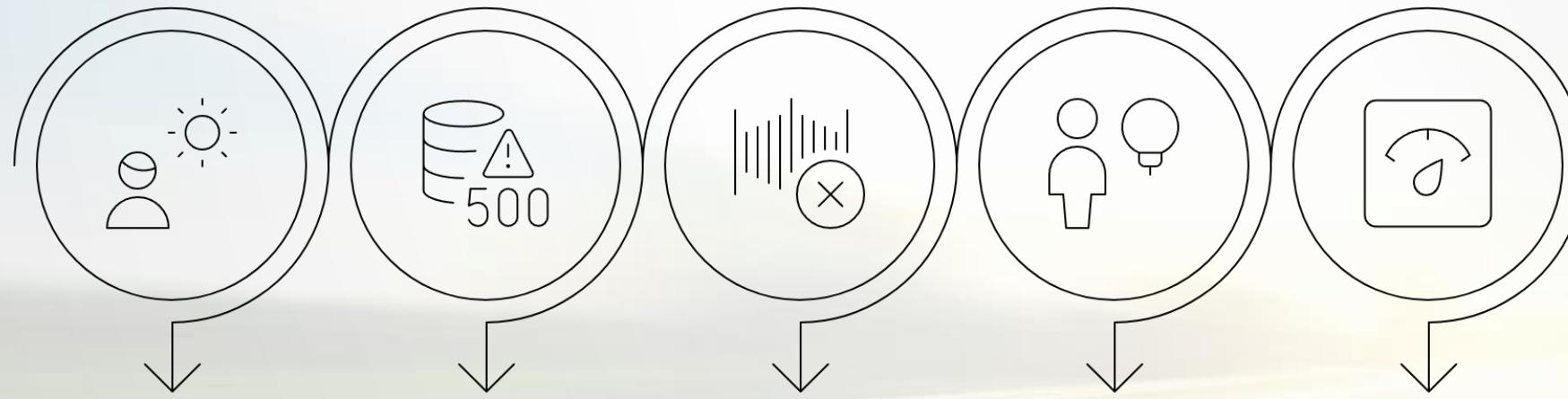


- **Opportunity:**
 - **Most corridors already have deployable CCTV cameras**
 - **Video cameras are widely used and information-dense**

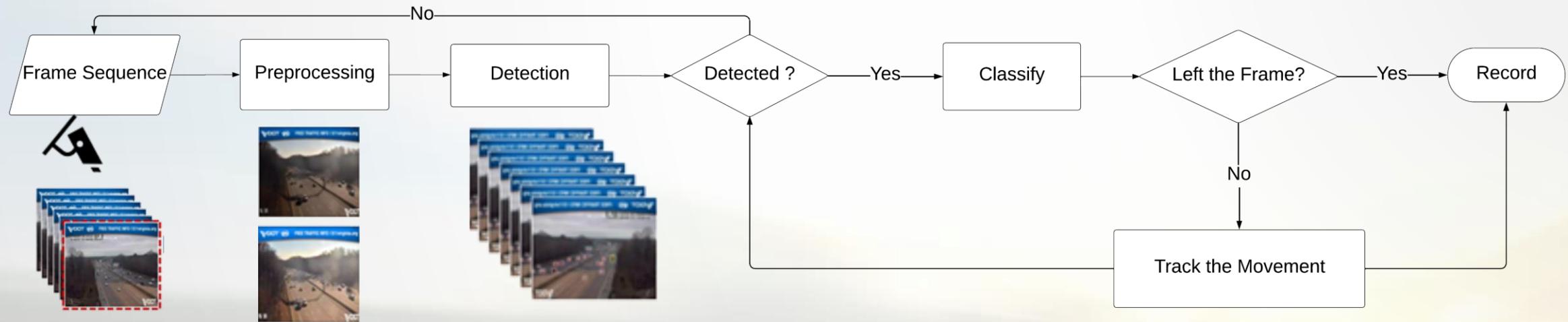
CCTV: closed circuit television



Algorithmic and Developmental Constraints in ML-Based Detection



Machine-learning algorithm with advanced preprocessing



1

Detection

- Provides accurate detection and vehicle counting over extended periods.
- Optimized for favorable conditions (e.g., daytime with clear weather).

2

Classification

- Currently supports basic vehicle classification:
 - Auto
 - Truck (All Types of Truck, Pickup truck, Van)

3

Directional

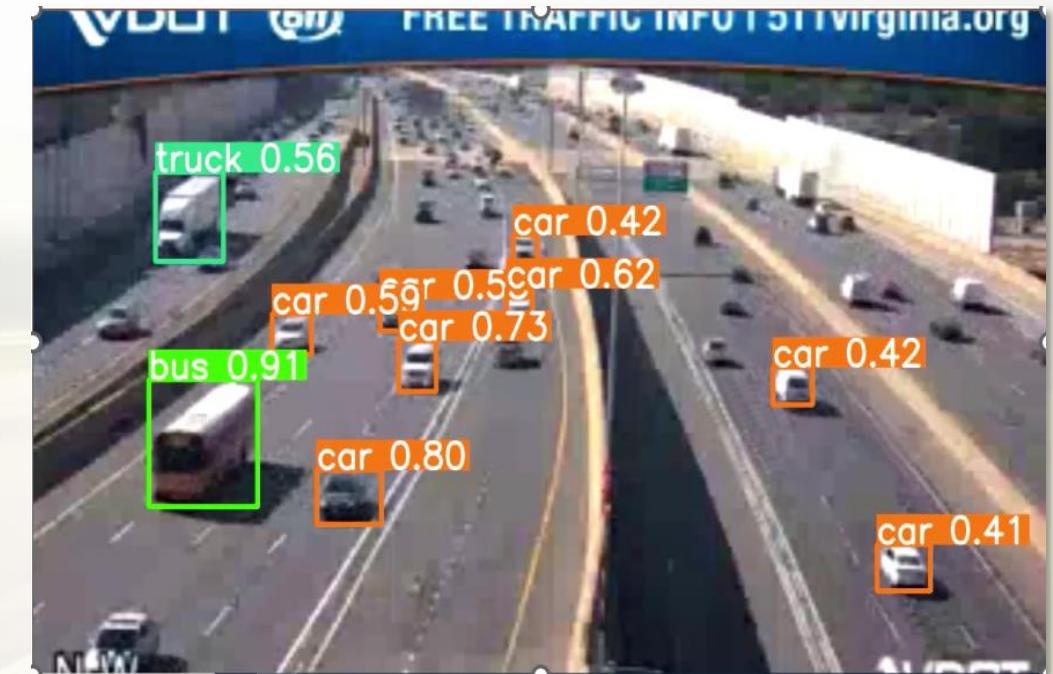
- Automatically determine the direction of travel.

4

Optimization

- Image processing techniques to increase image quality:
 - Challenging weather conditions
 - Low-light scenarios, including dusk and nighttime
 - Lens-related issues (e.g., droplets or dust)

- **State of the Art Model** YOLOv8 provides real-time object detection with high accuracy and speed
- **One-Stage Detector:** Directly predicts bounding boxes and class probabilities
- **Multi-Class Capability:** Can detect and classify different vehicle types (cars, trucks)
- **Deployment Ready:** Lightweight for real-time traffic monitoring.
- **Training:** Pre-trained on COCO datasets
- **Development System:** Microsoft Windows 11 \ AMD Ryzen 5 6600H \ 63.2 GB RAM \ NVIDIA GeForce RTX 3050 Laptop GPU



YOLOv8 detection on a highway scene. Multiple vehicle classes labeled with confidence scores.

Network & Sites

CCTV on primary gantries across Northern Virginia commuter corridors

24/7 Capture & Sync

Continuous RTSP with FFmpeg / Clocks synchronized;
Local timestamps embedded in filenames and metadata

Segmentation & Encoding

Stream is cut into 15-minute clips; CUDA for hardware-accelerated decode/encode

Parallel Processing

Multi-location capture workers run in parallel with retry/back; health checks for bitrate, FPS, and latency.

Quality Assurance

Automated flags black/blank frames, excessive jitter and drop-frame rates; alerts trigger re-capture

Output

Per-clip stores camera ID, with a consistent path schema:
site id/YYYY/MM/DD/HH:MM/

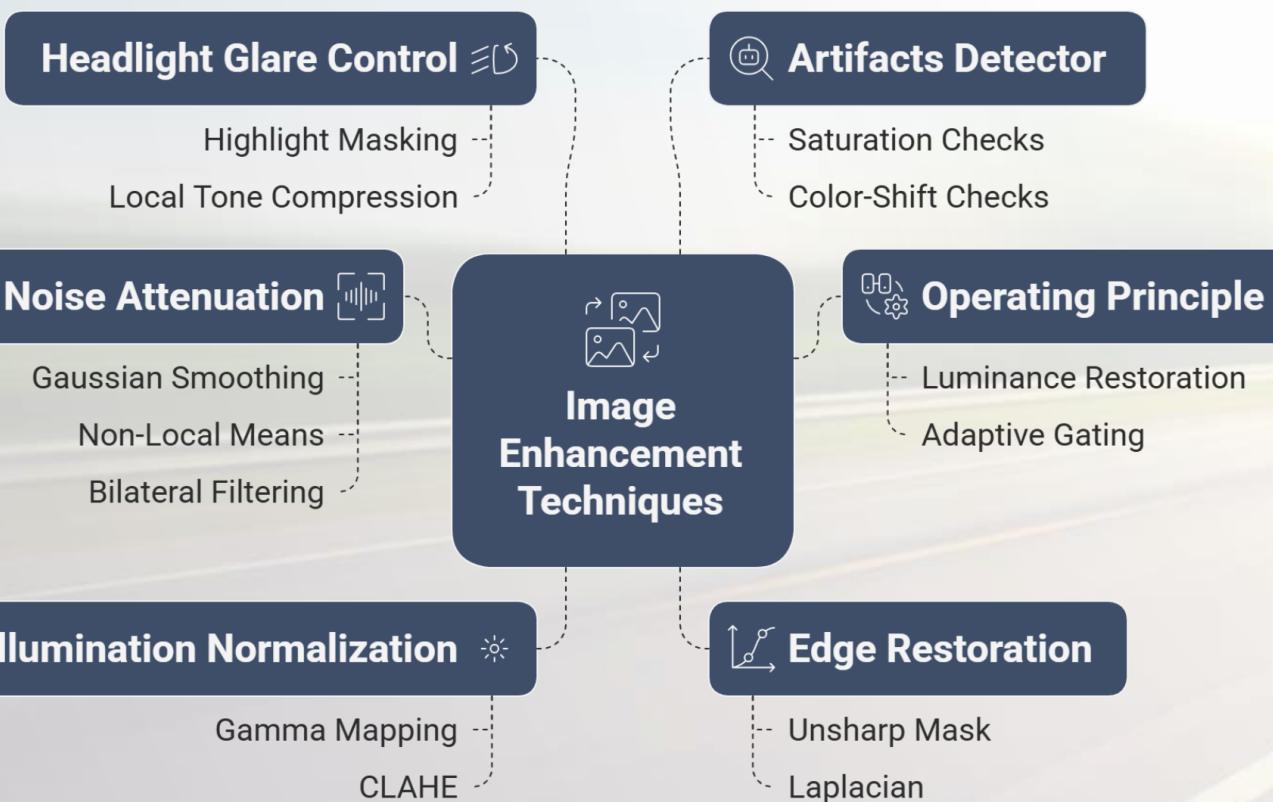


On-frame metadata overlays (date/time, camera ID, mile-marker, direction, elapsed time) parsed per clip for synchronization



Example of low-quality data dropped during the quality check

RTSP: Real-Time Streaming Protocol | FFMPEG: Fast Forward Moving Picture Experts Group



CLACHE: Contrast Limited Adaptive Histogram Equalization



Raw versus enhanced frames, showing improved contrast and clarity.

Duplicate handling

Retain the highest-confidence detection per ID and merge short-lived duplicates.

Temporal buffer

Keep the last 10 centers per ID to smooth noise.

State labeling

Classify each track as approaching, moving away, or stationary.



Inputs

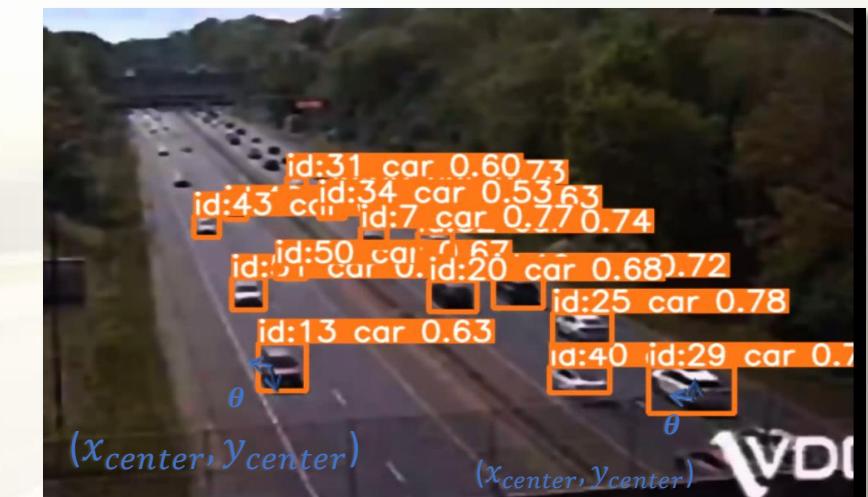
Per-frame detections with ID and box normalized by image size.

Position & direction

Use the bbox center and assign corridor direction from camera orientation.

Motion vector

Compute angle and step size from frame-to-frame center displacement; apply an adaptive threshold to ignore micro-jitter.



Trajectory detection from YOLO tracks. Motion vector analysis estimates each vehicle's position, direction, and state.



Video Example of Detection and Classification with Enhancement Using Yolo



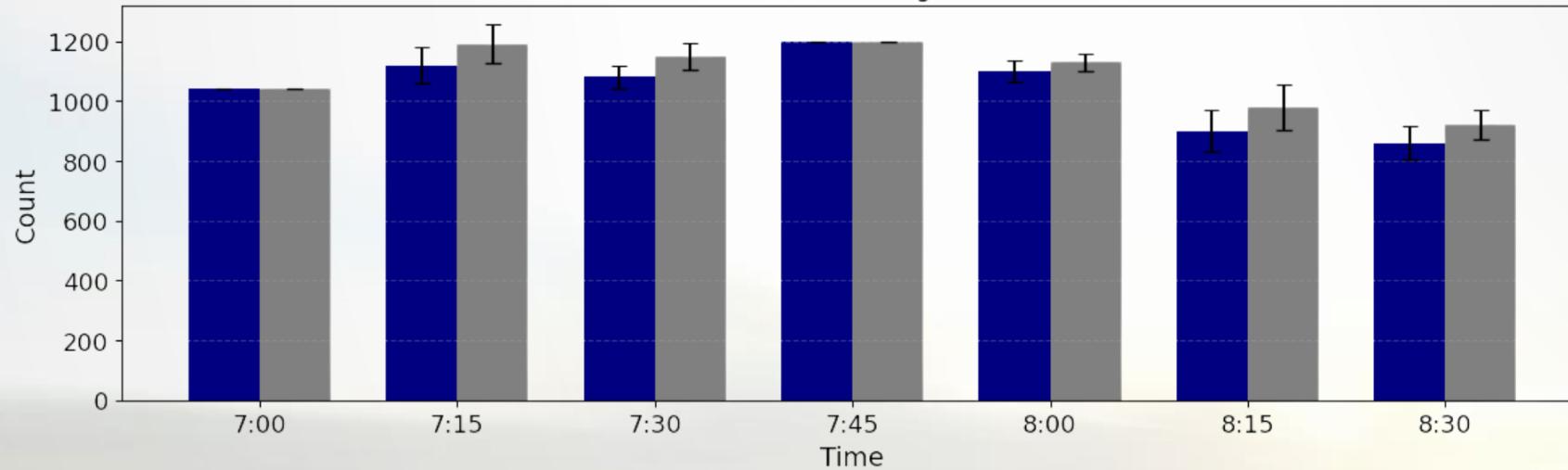
Evaluation of the Vehicle Detection Algorithm in Rainy Weather After Enhancement



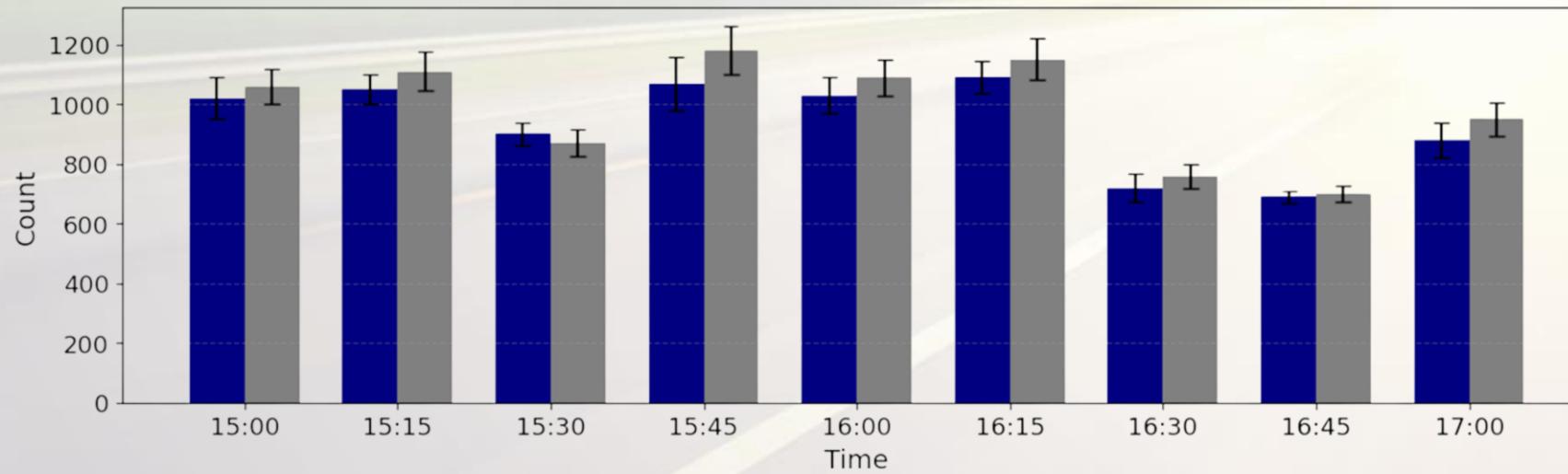
Example of Enhanced Images with Low Brightness and Contrast
Nighttime (left) and Dusk (right)

■ Ground-Truth Count (Manual) ■ Algorithm Output (Automated)

Vehicle Counts — Morning Peak Window



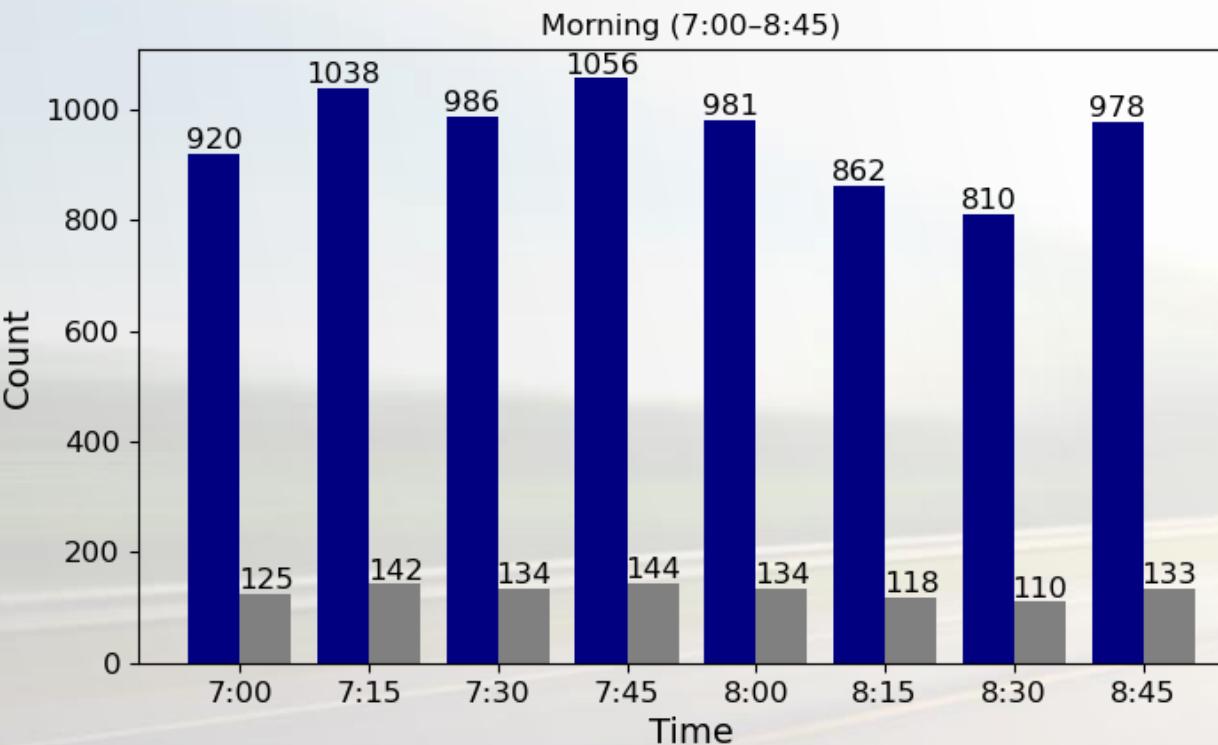
Vehicle Counts — Afternoon Peak Window



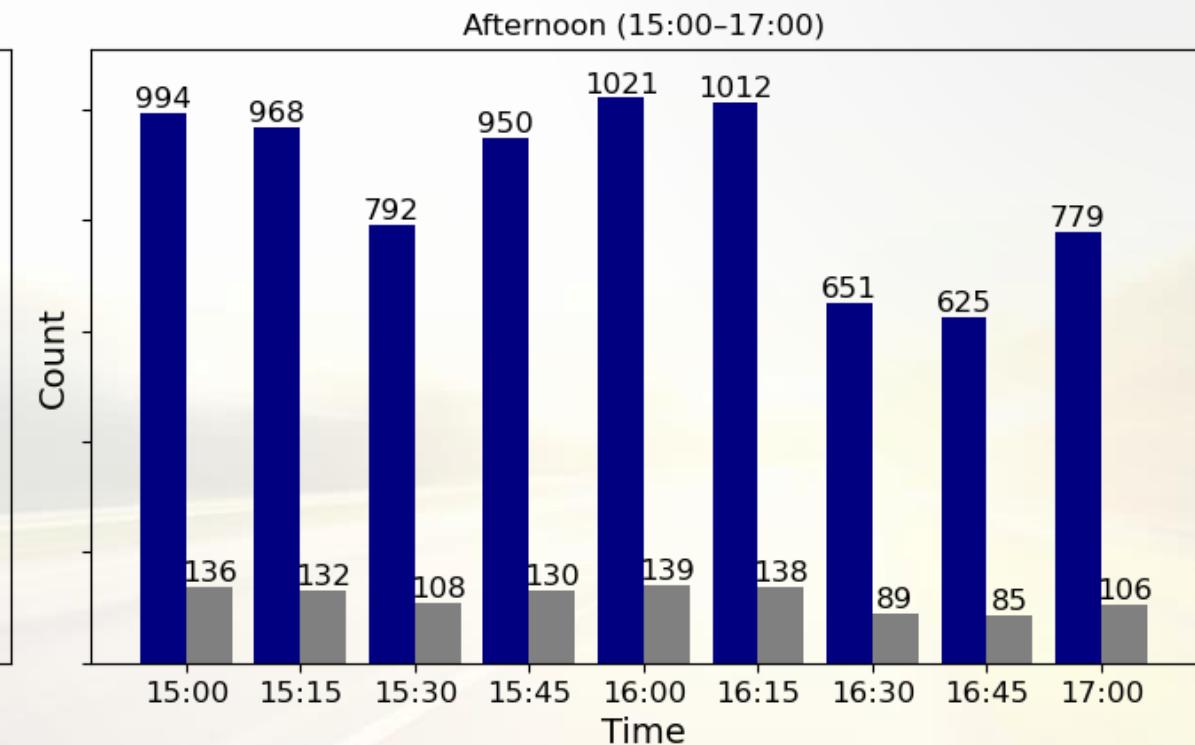
**Comparative Analysis of Manual and Automated Vehicle Counts at Three Locations on I-66 Inside the Beltway (I-66) in VA.
Morning Sessions (top) and Afternoon Sessions (bottom).**

Note: Error bars represent variability in vehicle counts.

Auto Truck



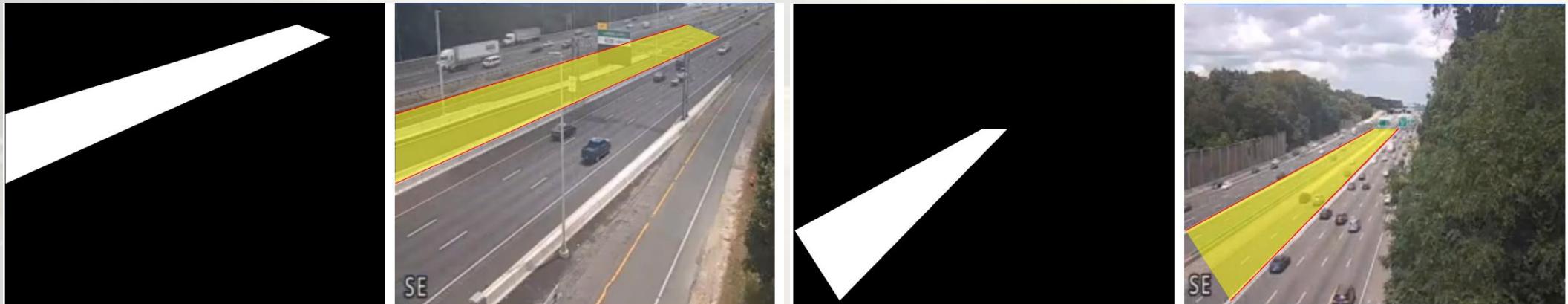
Auto Truck



Auto vs. Truck counts by 15-minute interval, shown for (left) morning and (right) afternoon for I-495 in VA.

- **End-to-end automation**
 - Continuous acquisition → enhancement → YOLOv8 + BoT-SORT → trajectory reconstruction
- **Real-time, GPU-accelerated**
 - CUDA deployment, scalable across corridors
- **Robust preprocessing and Trajectory identification**
 - Illumination normalization, denoise/deblur, and glare control improve detector/track stability under adverse conditions
 - Ground plane mapping work without predefined ROIs, simplifying field deployment
- **Portable across cameras**
 - Handles varying orientations, focal lengths, and resolutions with minimal re-tuning
- **Cost-effective**
 - Uses existing CCTV
 - Reduces manual counts and hardware upgrades
 - Minimal retraining for new sites

- Expand beyond basic vehicle classes (car, bus, truck)
 - Light/medium/heavy trucks
- Fine-tune and adjust the model for real-time deployment
- Lane-based traffic analysis based on different classes (Express Lane & GP Lane)



Lane Identification Mask and Overlay. Binary mask and color overlay for visual validation



Questions/Comments

Tara Diba, Ph.D. – Transportation System Modeler &
Data Analyst

tdiba@candm-associates.com