



# Artificial Intelligence–Aided Automated Detection of Railroad Trespassing

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Above: Approximately 95% of railroad deaths are due to trespassing and grade-crossing collisions. Artificial intelligence and video cameras may be a key to lowering that risk.

**A**t the 2018 American Public Transportation Association Rail Conference, Federal Railroad Administrator Ronald L. Batory encapsulated one of the biggest problems in the rail industry today, noting that “trespassing on railroad property is the leading cause of all rail-related deaths” (1). Ninety-five percent of railroad deaths on freight and passenger railroads between 2009 and 2016 were due to trespassing and grade-crossing collisions. The number of trespassing casualties from 2013 to 2016 was 16% higher than the number of casualties from 2009 to 2012 (2–4). In this research, trespassing is defined as incursions 1) at grade crossings, when roadway users enter after the signal lights have been activated, and 2) at right-of-way (ROW) locations that are neither intersections nor crossings, except by authorized railroad personnel (5).

Most rail trespassing behavior does not result in injuries or fatalities, however. Many instances of trespassing go unde-

tected or are not recorded in Federal Railroad Administration (FRA) safety databases because no immediate harm occurred. This lack of data prohibits comprehensive analyses of trespassing risk; although not all trespassing events cause damage, they indicate certain behaviors that may lead to severe consequences if repeated. Learning from trespassing is a critical element of effectively developing the three E’s of safety—education, enforcement, and engineering strategies—to prevent trespassing on railroad tracks (6).

## Trespassing and Big Video Data

Greater availability of video data in the rail industry has made it easier to acquire trespassing data. Closed-circuit television (CCTV) cameras can be found throughout railroad yards, bridges, grade crossings, and stations. In 2015, the Fixing America’s Surface Transportation Act mandated the installation of cameras throughout passenger railroads to promote safety objectives;

Long Island Rail Road's Farmingdale Station is equipped with CCTV cameras to monitor activity around the tracks.

ever since then, the deployment of CCTV systems in the United States has increased (7). For example, in Palo Alto, California, Caltrain has installed CCTV cameras at safety-critical grade crossings to monitor and prevent illegal incursions via an integrated alert system (8).

The CCTV trend is global. For example, in 2018 India began an initiative to install cameras on more than 11,000 trains and in 8,500 stations throughout the country (9).

These cameras provide valuable video-based sources of big data for railroads—but analyzing the data accurately in real time is a challenge. At present, many camera systems are reviewed manually by railroad staff, but limited resources and operator fatigue can lead to missed trespassing events (10–11).

## Artificial Intelligence for Trespassing Detection

This article presents research on an artificial intelligence (AI) algorithm that uses an existing video infrastructure to watch for, recognize, and understand trespassing events in real time. The algorithm is coupled to a live alert system that sends trespassing alerts to designated destinations.

Evidence from parallel industries that use similar algorithms, such as highway and aviation, indicate that AI can help current railroad staff detect more trespassing. The AI detection system outlined here combines two computer-vision AI techniques: region of interest (ROI) and Mask R-CNN.

ROI is a user-defined area in the camera's field of view that denotes a trespassing event if the area is entered by a person or vehicle. Mask R-CNN is an artificial neural network (that is, AI that mimics the network of neurons in the human brain) used for image recognition (12). For neural networks to function, they must be trained to recognize certain



Photo: Metropolitan Transportation Authority

objects. In this research, Mask R-CNN was integrated with the Common Objects in Context (COCO) data set, which consists of more than 328,000 labeled images of everyday scenes built for object-recognition research. This provides valuable training data for computer-vision algorithms to recognize commonly seen objects like people, cars, and trains (13).

As developed, the AI system parses a video live stream, prompts the user to identify the ROIs within the frame, detects whether people or vehicles are in the ROI, and sends alerts if trespassing has occurred.

### STEP 1: PARSING THE LIVESTREAM

The first step of the AI system is to establish a connection to the livestream of the selected location. After raw video data is provided—for example, via Internet livestream—the program will proceed to Step 2.

### STEP 2: DRAW ROI

The second step of the program is to identify the ROI. A user will be prompted with a static image of the video feed and then can select the outer limits of the trespassing area in sequential order. The borders of the ROI will be represented by a green line and can be closed by selecting the first point.

Multiple ROIs can be identified in the same frame and differentiation can be

made between ROWs and grade crossings (see Figure 1, page 32). The difference is that any object—for example, person, motorcycle, bicycle, car, or truck—detected within the ROW ROI will be deemed illegal and will trigger an alert, except for authorized railroad personnel. Conversely, the grade-crossing area only will trigger an alert if the algorithm detects that the signal lights are active.

### STEP 3: TRESPASSING DETECTION

The third step in the algorithm utilizes Mask R-CNN (12). Each frame is checked for objects within the selected ROI. If a grade-crossing ROI is identified, a subroutine will actively check for the initiation of a crossing signal light. As soon as that light activates, anyone who enters the ROI is considered to be trespassing. Both freight and passenger trains also are identified by the algorithm, but are deemed legal occupiers of the ROI and therefore do not trigger alerts.

One limitation of the algorithm is its inability to differentiate between authorized railroad personnel and trespassers. In future research, this will be resolved by providing the Mask R-CNN with training data to automatically filter out authorized railroad personnel and workers based on the unique characteristics of their attire. In the current system, these possible trespassing events are filtered out manually.





(a)



(b)



(c)

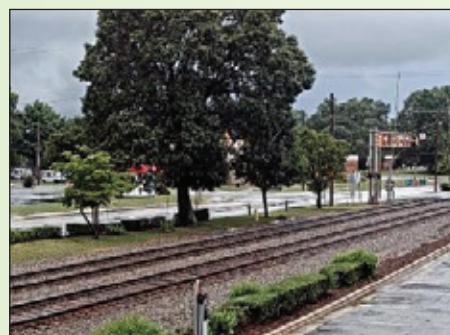
**FIGURE 1** ROI for (a) grade-crossing stream, (b) first ROW stream, and (c) second ROW stream. (ROW = right-of-way; ROI = region of interest.)



(a)



(b)



(c)

**FIGURE 2** Selected (a) grade-crossing stream, (b) first ROW stream, and (c) second ROW stream.

#### STEP 4: ALERT AND DATABASE POPULATION

The final step is twofold: 1) an alert text message or e-mail is sent to a designated user and 2) the trespassing event video and metadata are recorded to a database. The alert text messages or e-mails can be directed to railroad safety officials for immediate action. The database contains information on time, object detection, and identified zone (that is, grade crossing versus ROW), as well as the name of the associated video file.

#### Results

This system was tested on two different safety-critical scenarios: grade crossings and ROWs. Grade crossings are highway–rail intersections with active signalization that alerts pedestrians and vehicles to an approaching train. During a trespassing event at a grade

crossing, pedestrians and vehicles enter the crossing after the signal lights are activated. ROW locations are defined as railroad property with no intersection or crossing; in these locations, all incursions are deemed illegal except for those by authorized railroad personnel.

The study did not address passive grade crossings, which lack active signalization such as lights and gates, because of a lack of available video coverage of these locations.

A training and testing plan was put into place to ensure that the AI system achieved the highest accuracy and smallest number of missed detections and false alarms. First was initial development of the AI, using 130 hours of recorded grade-crossing footage. A known quantity of trespassing was established by manual inspection of the training data and then by debugging the AI until 100% accuracy was achieved.

To maximize accuracy, the AI system was tested on two new locations. Two ROWs were selected for this portion of the analysis and a cumulative 100 hours of live video were reviewed. The AI was not modified during this phase and a copy of the footage was reviewed to see if the system missed an instance of trespassing or if it raised false alarms. Longer, more diverse training data would increase the accuracy and adaptability of the AI in future research.

To select an appropriate stream, researchers searched for several variables, including a clear view of signal lights for grade crossings and an urban population, to increase the chance of trespassing events (14). With these factors considered, three streams were identified for analysis. Figure 2 (above) shows a typical view of the locations.

A grade crossing in Ashland, Virginia, and two ROWs in Thomasville, North Carolina, were chosen for two reasons: 1)

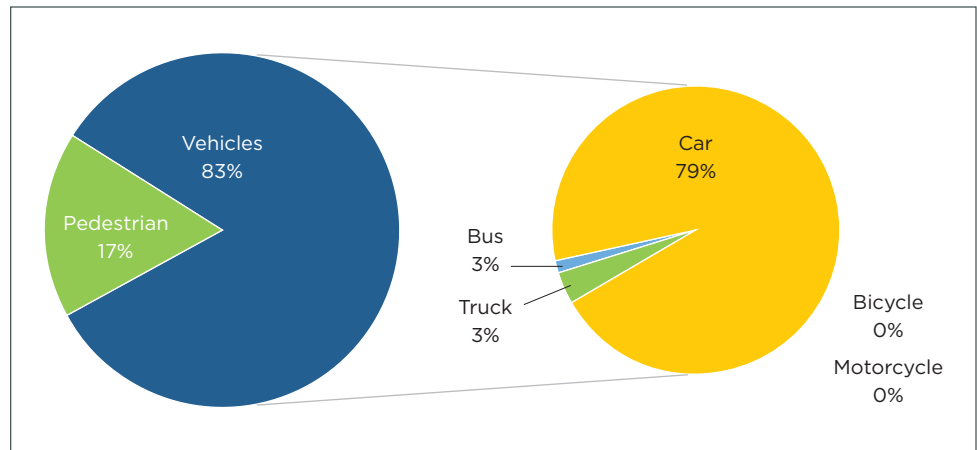
availability of video streams with a clear view of signal lights and 2) demonstration of the flexibility to different trespassing environments.

## Ashland, Virginia

Between July 19 and 25, 2018, 120 hours of live footage of the Ashland grade crossing were analyzed. The alert system reported 140 positively identified trespassing events. The analysis period included a range of environmental conditions, including heavy rainfall, fog, and many day–night cycles.

The AI system was able to automatically differentiate among types of trespassers. Figure 3 (at right) shows a breakdown of the results acquired during the analysis period. This graph represents the results during the limited duration testing and does not indicate a general trend. With a longer analysis period, this system could ascertain general trespasser demographics and trends. The AI algorithm searched for six categories of trespassers—car, truck, bus, person, bicycle, and motorcycle—selected from more than 80 object categories allowed by Mask R-CNN and the training data from the COCO data set (12, 13).

The most common type of violation observed in the study was the passage of vehicles through the grade crossing while the signalized intersection lights were activated. A total of 116 events of this kind were detected—comprising 83% of all



**FIGURE 3** Distribution of Ashland, Virginia, grade-crossing trespassers by type, based on 120 hours of sample video data.

detected trespassing events at the study location. Figure 4 (below) shows several typical examples of this type of detected event. The color overlay of the vehicle, automatically generated by the AI, indicates a recognized object. The masking also preserves the privacy of detected trespassers.

The second most common trespassing event, shown in Figure 5 (page 34), was the illegal incursion of pedestrians while the active signalized gates were down. These events, 24 in all, made up 17% of all detected trespassing events at this location.

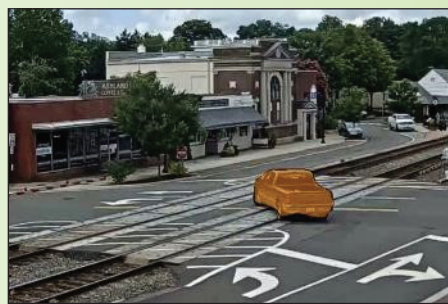
Both types of trespassing events represent typical nonconforming behaviors at grade crossings. Drivers and pedestrians who traverse the crossing while the gates are lowering appear to be confident that they have enough time to pass through

the intersection before the train arrives. Individuals who cross the intersection while the gates are raising assume that the crossing is safe, disregarding the possibility that a second train might approach and reactivate the gates.

These events were recorded to a local trespassing database. If such a database is expanded, commonalities between trespassing behaviors can be better understood. If the data gathered by the AI system indicate trends—for example, increased trespasser activity at similar time periods during the day—the presence of law enforcement may deter a large portion of illegal behavior (15). In another example, if it is discovered that most trespassing at the selected grade crossing occurs from a particular roadway direction, installing additional active signalization



(a)



(b)



(c)

**FIGURE 4** Vehicle (a) driving around deployed gates from far roadway, (b) driving around deployed gates from near roadway, and (c) school bus crossing as gates are closing.



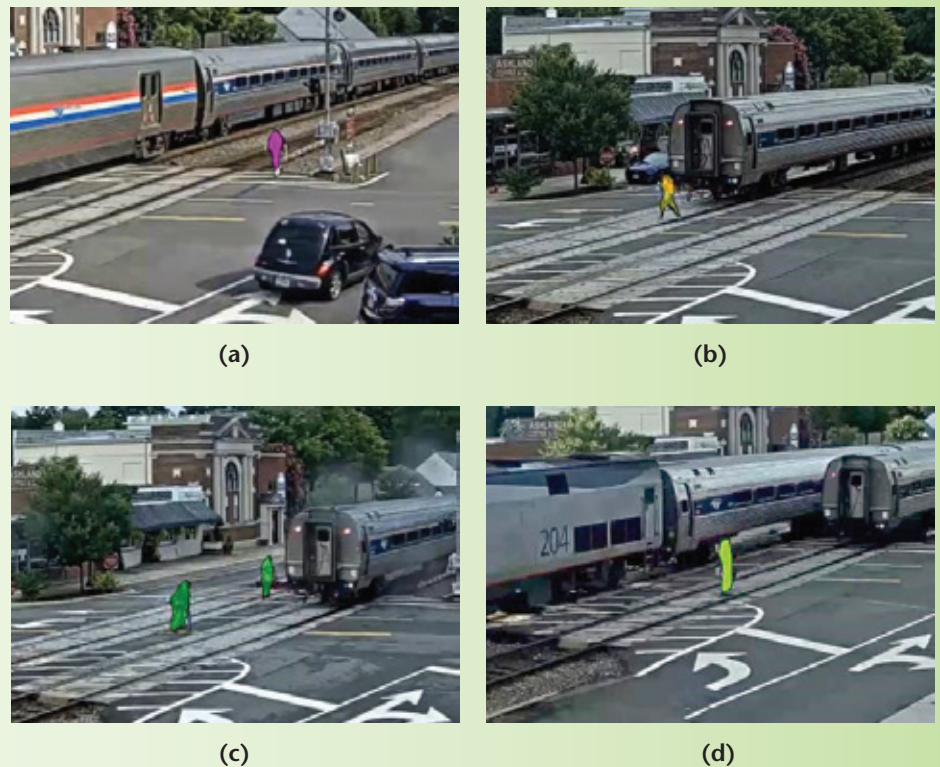
and barriers for traffic coming from that direction may mitigate excessive crossing (15). In the future, expanding this research to more locations and aggregating a large trespassing database could highlight trends and inform solutions to the trespassing problem.

An additional feature of the Mask R-CNN is its ability to anonymize trespassers automatically (12). The overlay of colored masks on the images of detected trespassers prevents the identification of the individual. Similarly, the masks overlaid on the images of vehicles obscure the license plate sufficiently to prevent identification, therefore maintaining the privacy of the driver.

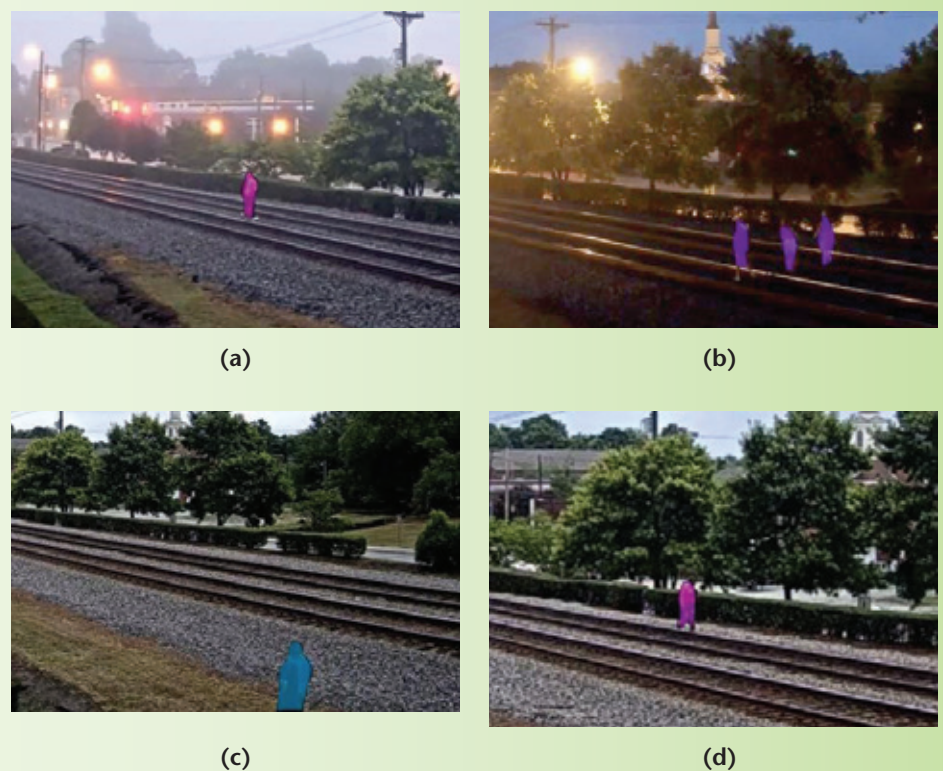
## Thomasville, North Carolina

In the final portion of the study, two completely new locations were tested with the AI system to demonstrate the flexibility of this algorithm to different trespassing scenarios. In the first ROW location, the AI analyzed 69 hours of live footage from July 21 to 27, 2018. During this period, the AI recognized 10 trespassing events in several distinct environmental conditions, including rain, fog, and nighttime (see Figure 6, at right). The AI was able to identify trespassers correctly, despite suboptimal detection conditions.

To date, the AI system is 100% accurate at this location; that is, producing no false positives and no false negatives. Most of the trespasses detected at this location show individuals walking along the railroad tracks instead of the sidewalk on the roadway to the north of the camera's view. It is unclear why these individuals made the choice to trespass on railroad tracks, but the aggregation of these events can inform proactive strategies for preventing accidents. A feature of the AI is the live-alert system that sends text messages or e-mails to a user-defined destination. In a trespassing scenario, it is conceivable for the AI to inform railroad staff that a trespasser is present on their property. At this point, law enforcement could be contacted and a trespasser could be removed before potentially catastrophic consequences occur (15).



**FIGURE 5** Single pedestrian (a) walking behind gates and (b) crossing behind train, (c) multiple pedestrians crossing behind train, and (d) single pedestrian waiting on railroad tracks.



**FIGURE 6** Single trespasser (a) detected crossing in foggy weather, (b) group of trespassers detected at night, (c) single trespasser detected before crossing, and (d) single trespasser traveling within railroad property.



(a)



(b)



(c)



(d)

**FIGURE 7** Trespasser (a) crossing tracks from parking lot to downtown area and (b) crossing in evening conditions, (c) adult and child trespassers crossing railroad tracks, and (d) two trespassers loitering on tracks near parking lot.

At the second ROW location, the AI system analyzed 48 hours of live footage between July 29–30, 2018, successfully detecting 109 trespassing events. The livestream view (Figure 7, above) overlooks a stretch of track leading to a grade crossing that can be seen at the far upper right of the screen. The detection of grade crossing–specific trespassing was impossible at this location because the view of the active signalization was obstructed and because of the extreme distance of crossing in the frame. Despite these limitations, a ROI was identified on the ROW and trespassing events were detected.

Some cases captured by the AI appear to show trespassers using the railroad property as a shortcut to travel between a parking lot and a downtown area. If aggregation of the data into a larger trespassing database shows this behavior to be a trend, it is possible to develop solutions to this trespassing problem (e.g., fencing). Additionally, the AI system can record changes in trespassing frequency before and after solutions are implemented, allowing for accurate countermeasure analysis.

Learning from trespassing can inform education, enforcement, and engineering solutions to the most severe safety problem faced by the railroad industry today.

## Conclusion

This research tested a customized AI algorithm for automated trespassing detection based on big video data in the railroad industry. Previously, collecting and analyzing camera video data for railroad trespassing was very laborious. With this AI technology, it is possible to compile large data sets of trespassing events and provide useful insights into trespassing behavior to ultimately support risk mitigation decisions.

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