U.S. Department of Transportation

Federal Railroad Administration

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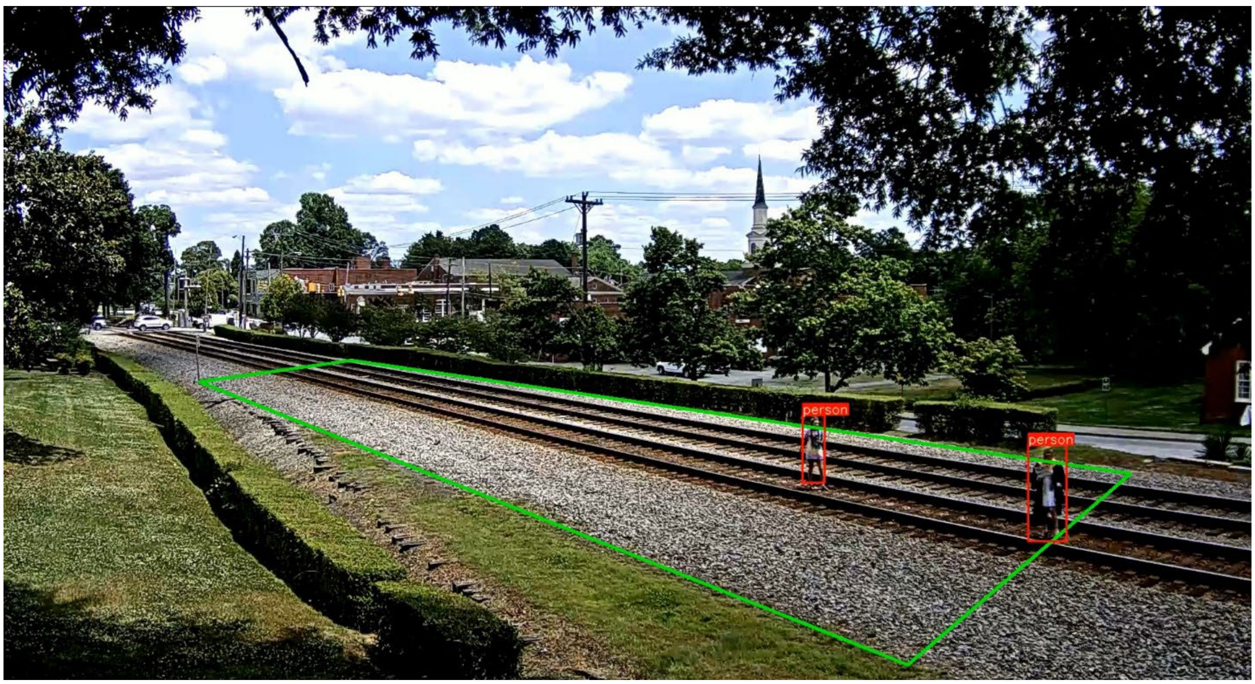
Washington, DC 20590

Development of Railroad Trespassing Database Using Artificial Intelligence



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14. ABSTRACT
The Federal Railroad Administration (FRA) sponsored a research team from Rutgers University to develop a proof-of-concept Trespassing Database using Artificial Intelligence (AI) technology to automatically process large volumes of live or recorded video data. The team used the Rutgers AI algorithm to analyze over 27,000 hours of live video data and 1,176 hours of recorded video data from rights-of-way and grade crossings at 11 locations in 6 states. The AI algorithm collected trespassing-related data, including traffic, rail signal activations, train events, and trespass events. Trespass event data were automatically collected for each trespasser, including date, time, type (e.g., person, car, truck, bus, motorcycle), weather, trespasser's path, and a video clip. The team manually validated all trespass event detection results to ensure that accurate data was included in the database. Over 29,000 trespass events were detected by the AI algorithm across all studied locations in this research.

This report also presents two year-long, in-depth case studies of one grade crossing in New Jersey (21,202 trespass events) and one right-of-way (ROW) location in North Carolina (476 trespass events). This report provides temporal and spatial analyses of trespass events and discusses AI-informed mitigation strategies.

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METRIC/ENGLISH CONVERSION FACTORS

ENGLISH TO METRIC

LENGTH (APPROXIMATE)

1 inch (in)	=	2.5 centimeters (cm)
1 foot (ft)	=	30 centimeters (cm)
1 yard (yd)	=	0.9 meter (m)
1 mile (mi)	=	1.6 kilometers (km)

AREA (APPROXIMATE)

1 square inch (sq in, in^2)	=	6.5 square centimeters (cm^2)
1 square foot (sq ft, ft^2)	=	0.09 square meter (m^2)
1 square yard (sq yd, yd^2)	=	0.8 square meter (m^2)
1 square mile (sq mi, mi^2)	=	2.6 square kilometers (km^2)
1 acre = 0.4 hectare (he)	=	4,000 square meters (m^2)

MASS - WEIGHT (APPROXIMATE)

1 ounce (oz)	=	28 grams (gm)
1 pound (lb)	=	0.45 kilogram (kg)
1 short ton = 2,000 pounds (lb)	=	0.9 tonne (t)

VOLUME (APPROXIMATE)

1 teaspoon (tsp)	=	5 milliliters (ml)
1 tablespoon (tbsp)	=	15 milliliters (ml)
1 fluid ounce (fl oz)	=	30 milliliters (ml)
1 cup (c)	=	0.24 liter (l)
1 pint (pt)	=	0.47 liter (l)
1 quart (qt)	=	0.96 liter (l)
1 gallon (gal)	=	3.8 liters (l)
1 cubic foot (cu ft, ft^3)	=	0.03 cubic meter (m^3)
1 cubic yard (cu yd, yd^3)	=	0.76 cubic meter (m^3)

TEMPERATURE (EXACT)

[(x-32)(5/9)] °F = y °C

METRIC TO ENGLISH

LENGTH (APPROXIMATE)

1 millimeter (mm)	=	0.04 inch (in)
1 centimeter (cm)	=	0.4 inch (in)
1 meter (m)	=	3.3 feet (ft)
1 meter (m)	=	1.1 yards (yd)
1 kilometer (km)	=	0.6 mile (mi)

AREA (APPROXIMATE)

1 square centimeter (cm^2)	=	0.16 square inch (sq in, in^2)
1 square meter (m^2)	=	1.2 square yards (sq yd, yd^2)
1 square kilometer (km^2)	=	0.4 square mile (sq mi, mi^2)
10,000 square meters (m^2)	=	1 hectare (ha) = 2.5 acres

MASS - WEIGHT (APPROXIMATE)

1 gram (gm)	=	0.036 ounce (oz)
1 kilogram (kg)	=	2.2 pounds (lb)
1 tonne (t)	=	1,000 kilograms (kg)
	=	1.1 short tons

VOLUME (APPROXIMATE)

1 milliliter (ml)	=	0.03 fluid ounce (fl oz)
1 liter (l)	=	2.1 pints (pt)
1 liter (l)	=	1.06 quarts (qt)
1 liter (l)	=	0.26 gallon (gal)
1 cubic meter (m^3)	=	36 cubic feet (cu ft, ft^3)
1 cubic meter (m^3)	=	1.3 cubic yards (cu yd, yd^3)

TEMPERATURE (EXACT)

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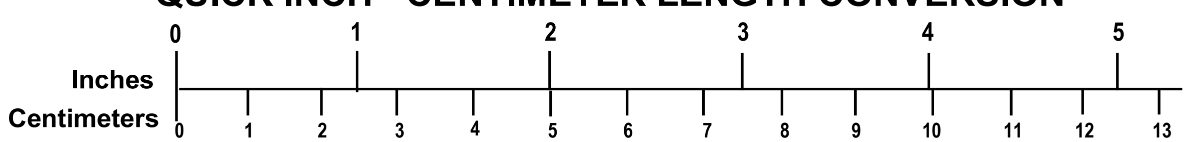
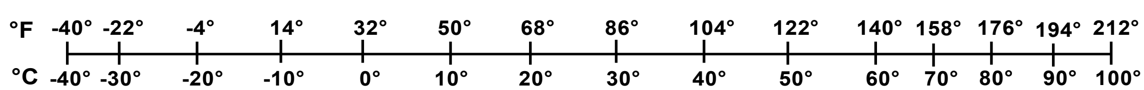
QUICK INCH - CENTIMETER LENGTH CONVERSION



QUICK FAHRENHEIT - CELSIUS TEMPERATURE CONVERSIO



For more exact and or other conversion factors, see NIST Miscellaneous Publication 286, Units of Weights and Measures. Price $2.50 SD Catalog No. C13 10286

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Executive Summary

Over the past ten years, trespassing fatalities at highway-rail grade crossings and on rights-of-way have accounted for around 95 percent of all fatalities in the railroad industry (U.S. Bureau of Transportation Statistics, 2019).

The Federal Railroad Administration (FRA) sponsored a research team from Rutgers University to develop a proof-of-concept Trespassing Database using Artificial Intelligence (AI) technology to automatically process large volumes of live or recorded video data. The team used the Rutgers AI algorithm to analyze over 27,000 hours of live video data and 1,176 hours of recorded video data from rights-of-way and grade crossings at 11 locations in 6 states. The AI algorithm collected trespassing-related data, including traffic, rail signal activations, train events, and trespass events. Trespass event data were automatically collected for each trespasser, including date, time, type (e.g., person, car, truck, bus, motorcycle), weather, trespasser's path, and a video clip. The team manually validated all trespass event detection results to ensure that accurate data was included in the database. Over 29,000 trespass events were detected by the AI algorithm across all studied locations in this research.

This report also presents two year-long, in-depth case studies of one grade crossing in New Jersey (21,202 trespass events) and one right-of-way (ROW) location in North Carolina (476 trespass events). This report provides temporal and spatial analyses of trespass events and discusses AI-informed mitigation strategies.

Additional analyses in this project can be found in the appendices. These include a one-year data analysis of a ROW location in North Carolina, a one-year data analysis of a grade crossing in Virginia, a three-week data analysis of two crossings in Louisiana, and a data analysis of near-miss records provided by one commuter railroad.

The results of this research and the new trespassing dataset can support FRA, railroads, and communities to better understand trespass event characteristics and potential influencing factors, thereby assisting in the development and evaluation of effective countermeasures. The AI-based technology developed in this project can provide important data to justify investments in informed engineering, enforcement, and education solutions for trespassing prevention, ultimately helping improve public safety.

1. Introduction

The Federal Railroad Administration (FRA) sponsored a research team from Rutgers University to develop a proof-of-concept Trespassing Database using Artificial Intelligence (AI) technology to automatically process large volumes of live or recorded video data. This AI system automatically generated key metadata and video clips by analyzing video live streams and recorded video data from grade crossings and rights-of-way (ROW). The system collected traffic data by class, train event data, signal activation data, and trespass event data. Data were automatically collected for each trespass event, including date, time, type (person, car, truck, bus, etc.), weather, trespasser's path, and a video clip. All results in the database were manually reviewed by the Rutgers team to ensure accuracy. False positive and false negative results were used to further improve the AI system throughout the study's duration.

1.1 Background

Trespass fatalities on railroad ROW and fatalities at highway-rail grade crossings have accounted for an average of 95 percent of all fatalities in the railroad industry in the past 10 years (U.S. Bureau of Transportation Statistics, 2019). A highway-rail grade crossing is defined by FRA as "a location where a public or private road, street, sidewalk or pathway, intersects railroad tracks at the same level" (Federal Railroad Administration, 2013). In the context of this report, a trespass event is defined as an event where unauthorized people or vehicles are in an area of railroad property (ROW) not intended for public use or enter an active signalized highway-rail grade crossing after it has been activated.

A prior study summarized FRA safety statistics, showing that from "2012 to 2016, trespass accidents in the United States cost railroads and society approximately $43 billion, a sum that did not cover indirect costs (e.g., emotional distress or productivity losses)" (Zhang et al., 2022). FRA emphasized the importance of this issue in 2021, stating that "trespasser deaths on railroad rights-of-way and other railroad property are the leading cause of fatalities attributable to railroad operations in the United States. To address this serious issue, the railroad industry, governments (Federal, State, and local), and other interested parties must know more about the individuals who trespass" (Federal Register / Vol. 86, No. 48, 2021). FRA Administrator Amit Bose urged that "we must discourage trespassing and encourage pedestrians and motorists to always obey signs and signals along the railroad right of way and to always expect a train" (Wanek-Libman, 2022). This issue persists for railroads across the United States. For example, New Jersey Transit's (NJT) CEO Kevin Corbett stated, "there's been a recent increase in grade crossing incidents on our rail and light rail systems that warrants a simple, but stern, reminder – obey all safety and traffic signals" (Medina, 2020).

Railroads have addressed this challenge through a combination of engineering, education, and enforcement campaigns. The 2015 Fixing America's Surface Transportation Act included a directive to install cameras throughout the rail industry, which resulted in rapid growth in the number of deployed camera surveillance devices (Fixing America's Surface Transportation Act, 2015). For example, in 2021, Chicago Metro planned to install cameras at 300 crossings and depots along its Southwest service and Rock Island lines (Popke, 2021). TriMet in Portland, Oregon, also planned to install camera systems "to document risks and incidents at grade crossings on its MAX light-rail system" (TriMet, 2020). In New Jersey, NJT was awarded a $2,339,700 Transit Security Grant to purchase "500 single-and multi-sensor cameras as well as specialized video-recording equipment" (Medina, 2020). In California, the Los Angeles Metro Transit Authority began using video cameras for law enforcement at grade crossings which "use high-resolution cameras to photograph motorists driving under or around railroad crossing gates" (Federal Railroad Administration, 2016). In the New York metropolitan area, Metro-North and the Long Island Railroad received $5 million for grade crossing improvements. Approximately 40 percent of those funds were committed to installing a CCTV system at 43 high-risk grade crossings (Metro Transit, 2017).

These cameras are a source of big data that can be used to better understand trespass behaviors. However, monitoring these video feeds and extracting useful information from them demands prohibitive amounts of manual labor. However, there has been a constant and rapid development of video-based AI algorithms, such as Mask Regional Convolutional Neural Network (Mask R-CNN) (He et al., 2018) and You Only Look Once (YOLO) (Redmon et al., 2016), which can read, recognize, and "understand" certain behaviors in video feeds.

It is necessary to understand more about railroad trespass events, and the growing amounts of untapped big data can be used to inform better solutions. The intransigent trespass challenge, the continued deployment of railroad video infrastructure, and the rapid development of vision-based AI present a research gap. The research team sought to fill this gap using state-of-the-art, vision-based AI to watch, recognize, and analyze railroad big video data in real-time to understand trespass events and develop precise engineering, enforcement, and education strategies. The database created in this research covers over 50,000 hours of live AI analysis in 11 locations across 6 states. Additionally, one rail agency's engineer-reported near-misses were analyzed. This research is the first long-term trespass event study of its kind.

1.2 Objectives

An objective of this research was to develop a Trespass Event Database (including trespass events that do not involve casualties) using AI technology developed by Rutgers University that can automatically process large volumes of video data. This new trespass event dataset can support FRA, railroads, and communities in better understanding trespass behaviors and influencing factors to develop and evaluate effective countermeasures.

The research team developed the following:

- A practical AI-aided methodology for real-time trespass event detection, trespass event data collection, and data analytics in support of trespassing prevention
- A proof-of-concept Trespass Event Database, based on real-time video data across multiple locations, including both grade crossings and ROW
- Insights and results drawing upon trespass event data collection and analysis
- A public web-based data dashboard and database allowing users to view, query, and display trespass event data and perform data analysis

1.3 Overall Approach

The AI system processed over 50,000 hours of live and recorded video data at nine grade crossings and two ROW locations in six states. Four locations, two crossings, and two ROW were analyzed for one year, while the other locations were each studied for approximately one week. Over 29,000 trespass events were captured during the study across all locations.

Two year-long, detailed case studies are presented in this report. In the first case study, 21,202 trespass events from a grade crossing in New Jersey were analyzed, yielding temporal trespass event heatmaps, trespass event summaries by season and month, a near-miss analysis, and a spatial analysis. In the second case study, 476 trespass events from one ROW location in North Carolina were analyzed, yielding temporal trespass event heatmaps, monthly trespass event trends, and a spatial trespass event origin analysis. AI data-informed solutions were presented for each location, using the trespass event database and the latest literature on solution effectiveness for justification.

Finally, the research team created a dashboard that was made available to the public to view and analyze the aggregated database.

1.4 Scope

This project focused on developing a proof-of-concept trespassing database using extensive video data through a customized AI algorithm for trespassing detection. For proof of concept, the project team selected 11 locations, including 9 grade crossings and 2 rights-of-way in New Jersey, Virginia, North Carolina, Connecticut, Louisiana, and Illinois. The team collected approximately one year of real-time trespassing data at four locations through live video streams: New Jersey Highway-Rail Crossing, Virginia Highway-Rail Crossing, North Carolina Right-of-Way North Camera View, and North Carolina Right-of-Way South Camera View. The duration of data collection and the diversity of location types allowed the researchers to analyze different trespassing behaviors across various rail types, climates, population densities, and grade crossing configurations. The team developed in-depth case study analyses for 6 of the 11 locations. Near-miss records from a commuter railroad partner also were analyzed and visualized from several perspectives.

1.5 Organization of the Report

This report is organized into seven sections and five appendices. Section 1 introduces the project's topic and goals. Section 2 provides a literature review of data collection research and AI techniques relevant to trespass event data collection. Section 3 describes the development and architecture of the artificial intelligence algorithm designed to capture trespass event data. Section 4 describes the data collection effort, covering the breadth and depth of the trespass event database. Section 5 presents trespass event data analysis for one grade crossing and one right-of-way case study with data-driven recommendations for trespass mitigation. Section 6 presents the publicly available dataset and analytic tool for reviewing trespass event trends. Section 7 presents the report's conclusions.

The appendices present concise data analyses of a Virginia Grade Crossing (Appendix A), a North Carolina ROW (Appendix B), a Louisiana highway grade crossing (Appendix C), and a Louisiana local road grade crossing (Appendix D). Appendix E presents additional research completed for this project on locomotive engineer-reported near-miss visualization.

2. Literature Review

2.1 Trespassing Research

The research team conducted a literature review to understand current practices for collecting and analyzing trespass event data at grade crossings and ROW in the railroad industry. A highway-rail grade crossing is defined by FRA as "a location where a public or private road, street, sidewalk or pathway, intersects railroad tracks at the same level" (Federal Railroad Administration, 2013). In the context of this report, trespass events are defined as situations where unauthorized people or vehicles are in an area of railroad property not intended for public use or enter an active signalized highway-rail grade crossing after it has been activated.

Trespass fatalities on railroad ROW and fatalities at highway-rail grade crossings have accounted for an average of 95 percent of all fatalities in the railroad industry in the past ten years (U.S. Bureau of Transportation Statistics, 2019). In addition to the lives lost, scheduling impacts, delays, and other unaccounted-for costs further increase the significance of this national issue. While trespass fatalities and the number of crashes at grade crossings are significant, they are the result of a series of precursory risky behaviors. Research projects by Zaman et al. (2018, 2019) and Zhang et al. (2018, 2022) have demonstrated that there are many more trespass events that do not result in accidents. However, these trespass behaviors can potentially yield negative consequences.

Zhang et al., (2022) conducted a literature review as part of that project's New Jersey Grade Crossing trespass event case study. This literature review outlines the state of the art in trespass event analysis and highlights the need to better understand trespassing. Figure 1 below shows a summary from this report of primary studies covering trespass events, categorized by severity.

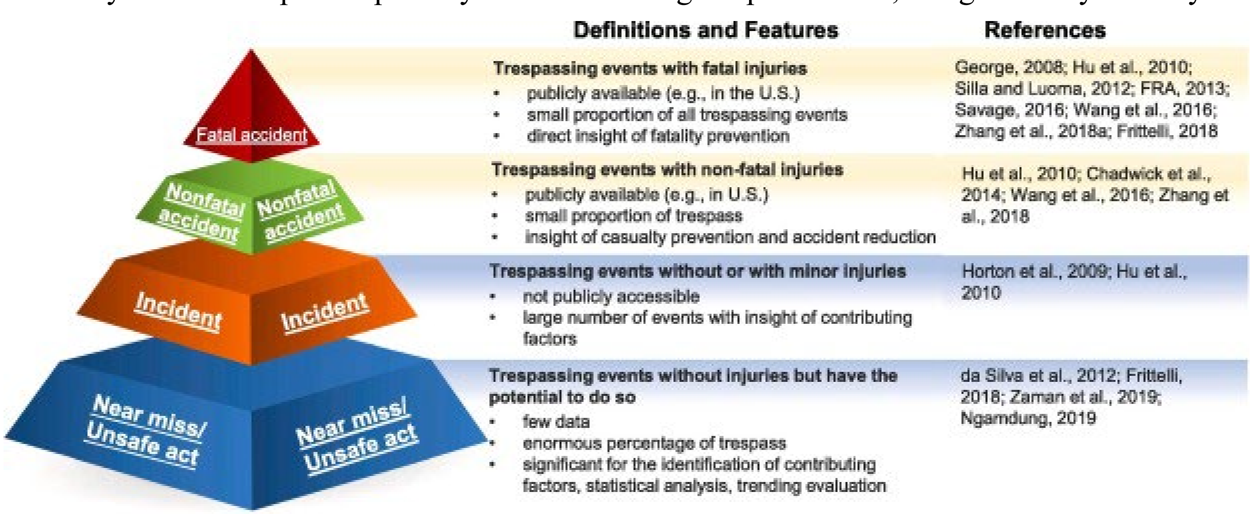


Figure 1. Pyramid Chart for Trespass Events Resulting in Fatal Accident, Nonfatal Accident, Incident, and Near-miss (Zhang et al., 2022)

This figure and the associated review show that there is a wide availability of data available to conduct extensive research on casualties. However, less is known about trespass events that do not lead to injuries or fatalities. Furthermore, Zhang et al. (2022) state that "much of the academic literature on trespassing risk is inconclusive due to limited data and uncertain data quality" and "there is a definite need for research analyzing near-miss events to figure out how to mitigate highway-rail grade crossing and right-of-way risks more efficiently" (Zhang et al., 2022).

Trespass event data is mostly collected and analyzed manually. A study was conducted by DaSilva et al. (2012) between 2001 and 2004 wherein a motion-activated system was installed to record trespassers at a railroad bridge. In this study, a large amount of labor was required to review the footage and obtain true quantities for the number of trespassers. In 2019, Searcy et al. (2020) studied trespassing at several locations in North Carolina using thermal cameras. Similarly, the video data was manually annotated and logged by a team of researchers.

Hellman et al. (2007) reviewed video data to evaluate the effectiveness of four-quadrant gates and in-cab signaling for reducing trespassing and collisions in Groton, Connecticut. Ngamdung et al. (2019) evaluated the long-term effects of trespassing photo enforcement, where video clips of crossing violations were manually reviewed by city staffers in Orlando, Florida. In 2019, Baron et al. (2019) used video data to evaluate the effectiveness of in-pavement lights for improving grade-crossing driver compliance. In 2020, Bedini-Jacobini & DaSilva (2020) used a camera system to evaluate the performance of gate skirts for preventing pedestrians from walking under the pedestrian gates of an active signalized crossing. These studies yield important suggestions for how to design, improve, and evaluate trespass mitigation strategies. However, the effectiveness of manual review is limited. Studies have shown that after 20 to 40 minutes of active monitoring, video reviewers will suffer from "video-blindness" which reduces their ability to effectively complete their tasks (Dee & Velastin, 2008). While valuable, each of these studies was limited in duration due in part to the resources required to analyze more data.

2.2 Artificial Intelligence Techniques

The use of AI and computer vision has the potential to overcome the resource limitations associated with manual video reviewing. This type of technology has been explored previously in limited scope to detect trespassers in railroad scenarios. As early as 2004, a study by Sheikh (2004) at the University of Florida used computer vision to detect trespassers using techniques like background subtraction, blob analysis, and region of interest. Combining these techniques allows a computer to understand simple features and behaviors of moving objects. These same techniques were adapted by Zaman et al. (2018) and Zhang et al. (2018) to detect trespassers at grade crossings.

However, these basic computer vision techniques are limited. They can only analyze simple features and are vulnerable to changing environmental conditions (e.g., day vs. night, clear vs. inclement weather, etc.). AI algorithms have the potential to overcome these challenges, understand complex behaviors, and remain invariable in changing environmental conditions. Research by Zaman et al. (2019) used Mask R-CNN (an image recognition AI algorithm) to detect trespassers at railroad grade crossings. Additionally, the Volpe Center "developed an…AI software application for automating the detection of grade crossing violations and trespass activities from static camera video feeds" called Grade Crossing Trespass Detection Software or GCTD (Bedini-Jacobini & Ngamdung, 2022). As in the research by Zaman and Zhang, this software used R-CNN to detect trespassers, but differed by automatically detecting grade crossing activations and railroad property using algorithms like a ResNet50 feature extraction backbone and SqueezeNet for scene classification. While the GTCD processed archival video records, the software presented in this report processed video in real-time using video live streams.

The past decade has seen a rapid increase in the development of AI-driven computer vision algorithms. The development of deep convolutional neural networks (DCNN) for image classification by Krizhevsky et al. (2012) led to the development of a family of ever-improving object detectors: Regional CNN (Girshick et al., 2014), Fast R-CNN (Girshick, 2015), Faster R-CNN (Ren et al., 2017), and Mask R-CNN (He et al., 2018). This research branched into the development of a more efficient detection algorithm called You Only Look Once (YOLO). YOLO's advantage is its superior performance in recognizing and localizing objects with a single scan of the image (Redmon et al., 2016). Following its initial release, more efficient versions were developed: YOLO9000 (Redmon & Farhadi, 2017), YOLOv3 (Redmon & Farhadi, 2018), YOLOv4 (Bochkovskiy et al., 2020), and YOLOv5 (Ultralytics, 2020).

To fully detect and understand trespass events, objects must be recognized and tracked. While YOLOv5 can localize an object in a single video frame, it does not have the inherent ability to track that same object from frame to frame. A tracking algorithm was published by Bewley et al. (2017) called Simple Online Realtime Tracking (SORT). This algorithm allows for the tracking of an object based on its location, bounding box dimensions, and trajectory within a series of images or sequential video frames. Building on this foundation, research by Wojke et al. (2017) added a deep association matrix to SORT (DeepSORT), allowing for objects to be tracked by deep neural features (e.g., object shape, color, and other image recognition features). Note that there has been no formal publication of YOLOv5 because it is a version of YOLOv4 written in Python for greater efficiency and adaptability.

The research team adapted YOLOv5 and DeepSORT in this project to recognize and understand trespass events in live and archival video. These algorithms were selected for their superior accuracy and performance compared to all other available algorithms at the time of development. The methodologies, critiques, and results of all AI models discussed in the literature review are shown in Table 1. The terms used in the table are defined below:

- Frame per Second (FPS): the number of consecutive full-screen images displayed each second
- Average Precision (AP): $\mathrm{AP} = \int_{\tau_{min}}^{\tau_{max}} P(\tau)d\tau$ where $P(\tau)$ is the precision of detected objects whose confidences are greater than τ
- Mean Average Precision (mAP): $mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i,$ where AP_i is the average precision of i-th class and n is the number of classes
- Multiple Object Tracking Accuracy (MOTA): A measure of the accuracy of both the recognition and tracking of objects of interest

Table 1. Summary of Relevant Computer-Vision Algorithms

Paper	Objective	Dataset	Methodology	Result	Critique
DCNN (Krizhevsky et al., 2012)	Image classification	ImageNet	DCNN improves the generalization ability of CNNs by stacking inner layers. Prevents overfitting by randomly freezing inner neurons.	top-1 and top-5 error rates of 37.5% and 17.0%.	It lays a foundation for applying Deep Learning to Computer Vision tasks but is challenging to train.
RCNN (Girshick et al., 2014)	Object detection	Pascal VOC	RCNN uses selective search to extract regional proposals, and then localizes and classifies objects of interest from these proposals based on their CNN features.	53.3% of mAP in Pascal VOC 2012.	It is computationally expensive to train since it performs CNN inference on many regional proposals. The selective search during the training process is also time-consuming.
Fast RCNN (Girshick, 2015)	Object detection	Pascal VOC	Fast RCNN feeds the whole image to CNN and generates a feature map that can be used by all regional proposals via the ROI pooling layer. It also suggests several techniques to accelerate the training process, such as adapting pre-trained weights and a multi-task loss function.	65.7% of mAP in Pascal VOC 2012.	It outperforms RCNN in training speed and accuracy.
Faster RCNN (Ren et al., 2017)	Object detection	Pascal VOC MS COCO	A Region Proposal Network (RPN) is designed to predict bounding boxes and their confidences in one pass.	75.9% of mAP in Pascal VOC + MS COCO.	It replaces select search with RPN, therefore, it can be faster as the training continues.
YOLO v1-v3 (Redmon et al., 2016) (Redmon & Farhadi, 2017) (Redmon & Farhadi, 2018)	Object detection	Pascal VOC	YOLO proposes a loss function to allow joint training on classification and localization. It also suggests replacing the fully connected layer by batch normalization and a high-resolution classifier for faster inferencing.	66.4% of mAP in Pascal VOC. Faster than RCNN in inferencing.	YOLO has low recall (more missed detections) compared to RCNN methods.

Paper	Objective	Dataset	Methodology	Result	Critique
YOLOv4 (Bochkovskiy et al., 2020)	Object detection	MS COCO	YOLOv4 explores real-time object detection by selecting the optimal combination of models. It considers the tradeoff between performance and accuracy. They invented a Self-Adversarial training strategy and a method to mix four training images for data augmentation and modified the normalization method (collects statistics only between mini batches within a single batch), making it more efficient for training/inference.	43.5% of mAP in MS COCO, 65 FPS on Tesla V100.	It achieves a good tradeoff between inferencing speed and accuracy.
SORT (Bewley et al., 2017)	Multiple object tracking	MOT2015	SORT uses Kalman filtering and matching cascade to link bounding boxes and tracks.	33.4% of MOTA in MOT2015, 260 FPS on single core of an Intel i7 2.5GHz machine with 16 GB memory.	It depends on fixed geometric features. Therefore, it is likely to lose track of objects after occlusion.
DeepSORT (Wojke et al., 2017)	Multiple object tracking	MOT2016	DeepSORT adds CNN feature of detected bounding boxes as another factor in matching cascade.	61.4% of MOTA in MOT2016.	It is more robust at tracking objects after occlusion but runs slower than SORT.

3. Artificial Intelligence Algorithm Development

3.1 Trespass Event Detection System Framework

The Trespass Event Detection System functions according to three discrete steps, as described in Figure 2. The system is initiated when the user provides a link to a live video stream or a recorded video file. The system extracts the first frame and presents it to the user, who then draws the region of interest (ROI) and identifies the signal lights if the location is a grade crossing. There are three main components of the developed AI monitoring system: the signal light activation algorithm, object detection by YOLOv5, and object tracking by DeepSORT.

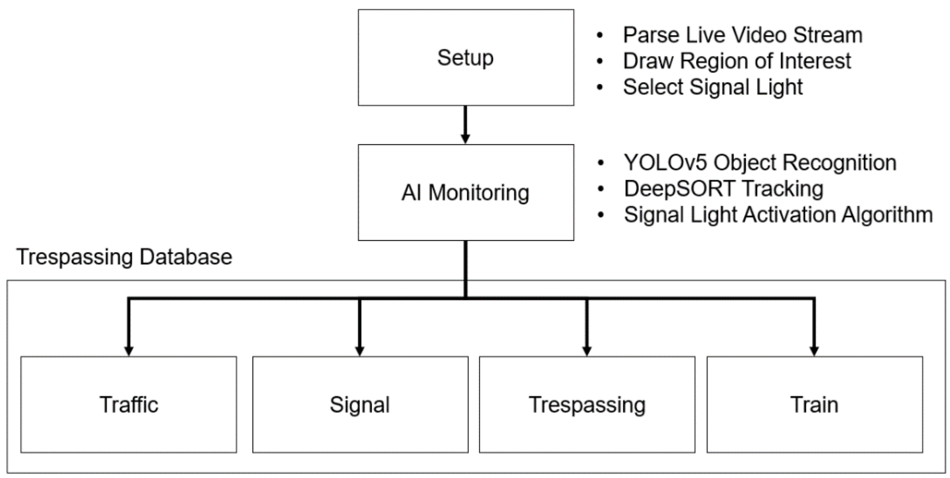


Figure 2. Trespass Event Detection System Framework

An ROI is a geometric shape within the video frame indicating the area where trespass events may occur. The ROI can be adjusted to include additional points and to match the user's needs and required geometry. An example of the user interface for the ROI and signal light selection can be seen in Figure 3.

Figure 3. Region of Interest and Signal Light Selection Example

In Figure 3, the red box shows the limits of the ROI, and the purple dots represent the region corresponding to the signal lights. Once the setup is completed, the algorithm begins recognizing and tracking objects. The system has four modules: traffic, signal, trespass events, and train.

3.1.1 Traffic Module

The traffic module recognizes objects using an adapted and custom-trained YOLOv5 algorithm. The objects are tracked using the DeepSORT algorithm (Bewley et al., 2016). If an object crosses the ROI, it is logged as a traffic event. The classification (e.g., car, person, truck, bus, etc.), weather, and time of occurrence are recorded in the database. Weather data are acquired by a third-party application program interface (API). The API allows for the automatic acquisition of weather data on demand. With this information, differences between the types of violators and behaviors can be discerned.

3.1.2 Signal Module

The signal module recognizes the state of the active grade crossing and determines whether it is activated. This is accomplished through a computer vision algorithm that determines the relative brightness of the signal lamp and compares it to the brightness of previous frames. When this module indicates that the crossing is activated, the trespass event module becomes active. The signal activation algorithm only activates after it observes 3 seconds of flashing, preventing false positives caused by illumination by headlights or other environmental factors. This delay also allows drivers and pedestrians already within the crossing or just perceiving the signals to clear the area before being counted as trespassers.

3.1.3 Trespass Event Module

Objects are recognized by the custom trained YOLOv5 and are tracked using DeepSORT. If the signals are active, trespass events are logged by the system. When the violator leaves the ROI, a clip of the video is saved to the database for later review and analysis. Once a trespass event is recognized, the following information is collected: uniquely generated ID, start time, end time, weather, type (e.g., person, car, truck, bicycle, motorcycle), and video clip link.

3.1.4 Train Module

Finally, trains are recognized and detected by the system using a custom trained YOLOv5 object class. This data is collected to help validate the system and to determine how close violators are to trains.

3.2 Signal Light Crossing Activation Detection Algorithm

The illumination of the signal lights is used to determine whether the grade crossing is activated. Activation is communicated by two alternatively flashing signal lights. The algorithm developed in this project is adapted from previous research by Zhang et al. (2018). In this prior research, the illumination levels of both signal lights were evaluated to determine whether the signal was active. Figure 4 shows an example of the intensity differences analyzed by the system during daytime and nighttime scenarios.

Figure 4. Intensity Difference of Stop Signal During Day and Night (Zhang et al., 2018)

This research further refined the approach to accommodate more environmental conditions encountered during a one-year live analysis. A refined computer-vision-based algorithm was designed to analyze the status following three main steps. First, the user identifies the positions of the centers of two signal lights in the video frame, marked as c_1, c_2 and the distances from the center to the boundary of the lamp and the shroud, marked as d_1, d_2. Second, the system establishes two squares encompassing the lamp and the shroud, given centers and distances. Third, the algorithm measures and compares the median illumination intensity of these two rectangles. If this illumination difference exceeds an established threshold, the signal is deemed to be active. Let $I_{i,j}^h$ be the hue saturation value (HSV) of the pixel in i-th row and j-th column.

$$conf(c,d) = median_{i=c_x-d}^{c_x-d}\, median_{j=c_y-d}^{c_y-d}\left(I_{i,j\,2}^h\right)$$

Note that the third digit of the HSV value, $I_{i,j\,2}^h$, represents the intensity.

In this algorithm, both lamps are analyzed independently and then joined to determine whether they are flashing in an alternating pattern. T is the empirically calculated threshold for determining if the signal lamp is bright.

$$activation = \begin{cases} true, & conf(c_1,d_1) - conf(c_1,d_2) > T \text{ or } conf(c_2,d_1) - conf(c_2,d_2) > T \\ false, & \text{otherwise} \end{cases}$$

This multi-part algorithm was designed to overcome the challenges of changing illumination levels, false positives due to vehicle headlights, and glare caused by sunlight.

3.3 Object Detection with You Only Look Once (YOLO)

Objects are recognized in the AI system by the YOLOv5 model. YOLO functions according to four steps: dividing the image, predicting bounding boxes, consolidating bounding boxes, and assigning confidence scores. It first divides the input image into a $S \times S$ grid. If the center of an object falls into a grid cell, that grid cell is responsible for detecting that object. Each grid cell predicts B bounding boxes and confidence scores for those boxes via YOLO networks. As shown in Figure 5, there are three components in the network: the backbone extracts deep CNN features, the neck layers collect feature maps from different stages, and the head is designated for bounding-box regression. The specific choice of models for each component can be found in the latest version of YOLO (Bochkovskiy et al., 2020, p. 4).

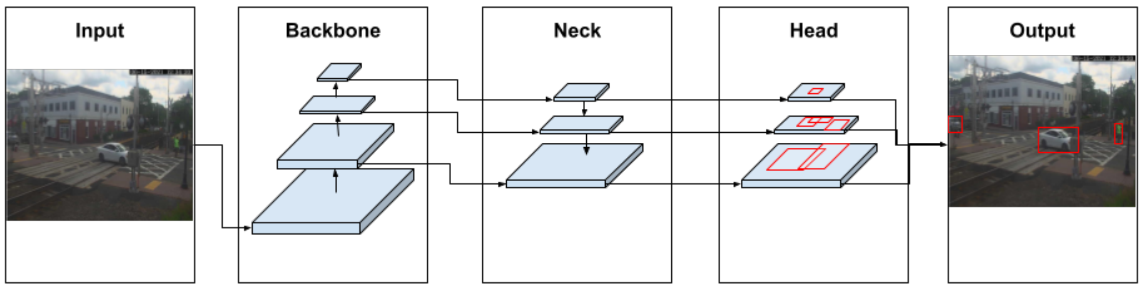


Figure 5. Illustration of YOLO Networks

Each bounding box consists of four coordinates: x, y, w, h. The (x, y) coordinates represent the center of the box relative to the bounds of the grid cell. The width and height are predicted relative to the whole image. Intersection Over Union (IOU) is used as a metric to evaluate confidence level and was used previously by Redmon et al. (2016). These confidence scores reflect how confident the model is that the box contains an object of interest.

Each grid cell also predicts C, where C is the number of predefined classes with conditional class probabilities $P\{Class_i|Object\}, i \in \{1,2,\dots,C\}$. These probabilities are conditional on the grid cell containing an object. It only predicts one set of class probabilities per grid cell, regardless of the number of boxes B.

Multiplying the conditional class probabilities by the individual box confidence predictions,

$$P\{Class_i|Object\} \times \{Object\} \times \ c = P\{Class_i\}c$$

provides class-specific confidence scores for each box. These scores encode both the probability that a class appears in the box and how well the predicted box fits the object.

3.4 DeepSORT Object Tracking

As seen in Figure 6, the YOLO output, including detected bounding boxes, corresponding confidence scores, and features, are input into the DeepSORT algorithm. A Kalman filter (Patel & Thakore, 2013) is used to predict the positions of the detected bounding boxes for the next time step. At the next time step, new detections are input, and the predicted tracks are processed following their status (i.e., confirmed or unconfirmed) to match the new detections.

The confirmed tracks are matched using the matching cascade algorithm. Matching cascade algorithms record the time duration of each track since the last update, and the newer tracks receive higher matching priority. For matching, the similarity of motion information (e.g., the position of bounding boxes) and the similarity of appearance features between predicted Kalman tracks and newly detected tracks are measured to obtain weighted similarities. The weighted similarities are input into the Hungarian algorithm (Kuhn, 1955), which is a widely used combinatorial optimization algorithm, to get a matching matrix. A matching threshold is used to get matched tracks and unmatched tracks. This method integrates multiple similarities and helps improve robustness against missed tracking due to partial occlusion (e.g., pedestrian passing behind a car).

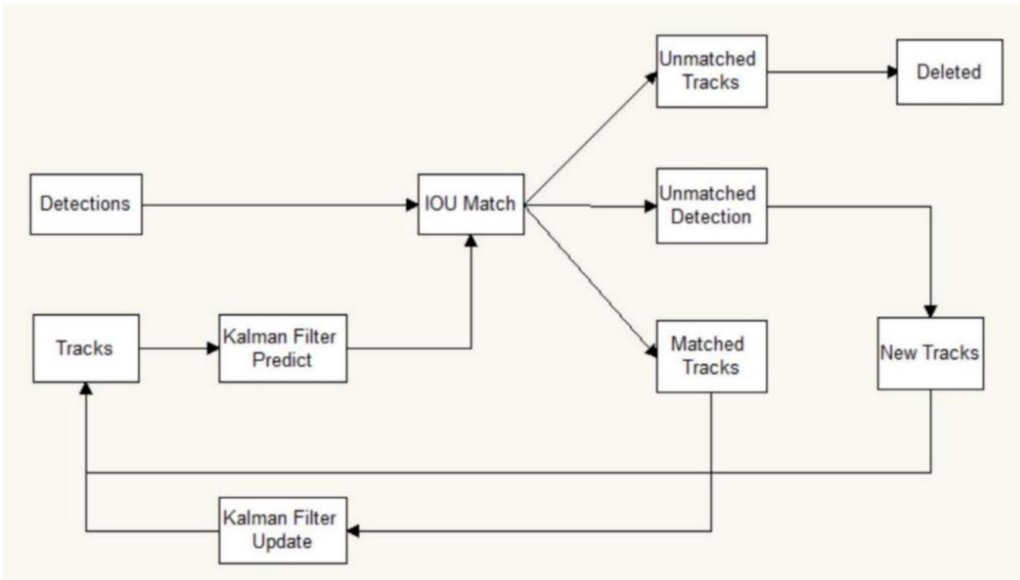


Figure 6. Flow Chart of DeepSORT (Liu & Juang, 2021)

Finally, unconfirmed tracks and unmatched tracks from the matching cascade phase are input into the IOU association algorithm to conduct matching with unmatched newly detected tracks. IOU values between unmatched tracks and newly detected tracks are calculated as a matching metric. IOU values are input into the Hungarian algorithm to get a matching matrix. A matching IOU threshold is used to acquire the matching results. This last step links previously detected objects in the past frames to detected objects in the current frame, allowing for continuous tracking of objects over time.

4. Data Collection

4.1 Selected Sites

Eleven sites were selected for analysis between 2020 and 2022 (Table 2). Nine grade crossings and two ROW were included in the database. The raw video data was a combination of live video streams and video recorded by the research team. Live video streams were obtained from a railroad collaborator and from Virtualrailfan (a railroad enthusiast video streaming website). Recorded data was obtained using a battery-operated camera system. Approximately one year of data was analyzed in real time from the livestream locations in New Jersey, Virginia, and North Carolina. The other locations had approximately one week of raw video data each.

The locations were selected based on live stream quality (i.e., video resolution and frame rate), availability (i.e., stream uptime), and discussions with railroad collaborators. Recorded locations were selected based on discussions with collaborators and the availability of existing infrastructure to temporarily install camera hardware.

Table 2. Selected Sites

State	Type	Tracks	Lanes	Traffic Type	Video
New Jersey	Grade Crossing	2	2	Commuter and Freight	Live
Virginia	Grade Crossing (Quiet Zone)	2	2	Freight and Intercity	Live
North Carolina	ROW	2	N/A	Freight	Live
North Carolina	ROW	2	N/A	Freight	Live
Connecticut	Grade Crossing	3	2	Intercity and Commuter	Recorded
Louisiana	Grade Crossing	1	2	Freight	Recorded
Louisiana	Grade Crossing	1	6	Freight	Recorded
Illinois	Grade Crossing	2	4	Commuter	Recorded
Illinois	Grade Crossing	2	2	Commuter	Recorded
Illinois	Grade Crossing	2	2	Commuter	Recorded
Illinois	Grade Crossing	2	4	Commuter	Recorded

4.2 Data Processing

Eleven locations were analyzed across six states as shown in Table 3. Recorded video was gathered intermittently between January 1, 2021, and January 31, 2022. The live streams were periodically unavailable due to system maintenance, so the full year was not captured.

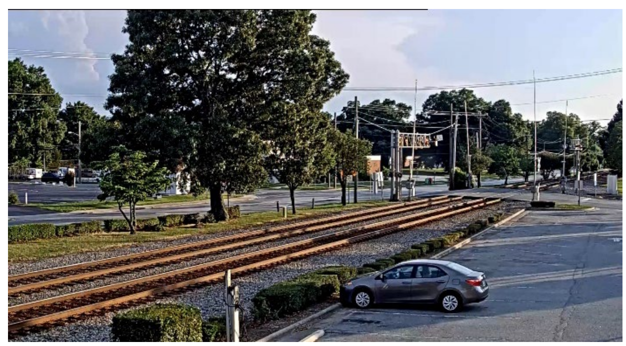
During this research, an internet protocol (IP) camera was installed on a utility pole located about thirty feet northwest of the New Jersey grade crossing, facing southwest toward the grade crossing. In this database, 272 days (6,582 hours) of live video data was analyzed (January 1st, 2021, to January 31st, 2022). This video stream was continuously monitored by the AI for 24 hours each day of the study period. However, the video stream was sporadically unavailable due to periodic maintenance and intermittent connection issues at the site. The video format is MP4 with a resolution of 704 x 576 pixels and a variable of 5 to 15 frames per second.

Other video streams were obtained from Virtualrailfan and had a video format of MP4 with a resolution of 1920 x 1080 pixels and 30 frames per second. Similarly, these video streams were sporadically unavailable due to periodic maintenance and intermittent connection problems. In total, 252 days (6,048 hours) of Virginia Crossing, 328 days (7,872 hours) of North Carolina ROW North View, and 302 days (7,248 hours) of North Carolina ROW South View live video data was analyzed. Typical views of the livestream locations can be seen in Figure 7.

Table 3. Data Collection Range

State	Start Date	End Date	Days	Trespass Events
New Jersey, Crossing	1/1/2021	1/31/2022	272	21,202
Virginia, Crossing	1/1/2021	1/31/2022	252	3,395
North Carolina, North Camera View	1/1/2021	12/31/2021	302	476
North Carolina, South Camera View	1/1/2021	12/31/2021	328	2,025
Connecticut, Local Road Crossing	1/19/2022	1/25/2022	5	234
Louisiana, Highway Crossing	6/9/2021	6/27/2021	15	762
Louisiana, Local Road Crossing	6/9/2021	6/28/2021	16	146
Illinois, Crossing 1	10/17/2022	10/19/2022	3	79
Illinois, Crossing 2	10/17/2022	10/19/2022	3	428
Illinois, Crossing 3	10/17/2022	10/21/2022	5	250
Illinois, Crossing 4	10/17/2022	10/18/2022	2	34

(a)



(b)

(c)

(d)

Figure 7. Typical Views of Livestreams from the (a) North Carolina ROW North View, (b) North Carolina ROW South View, (c) New Jersey Grade Crossing, and (d) Virginia Grade Crossing

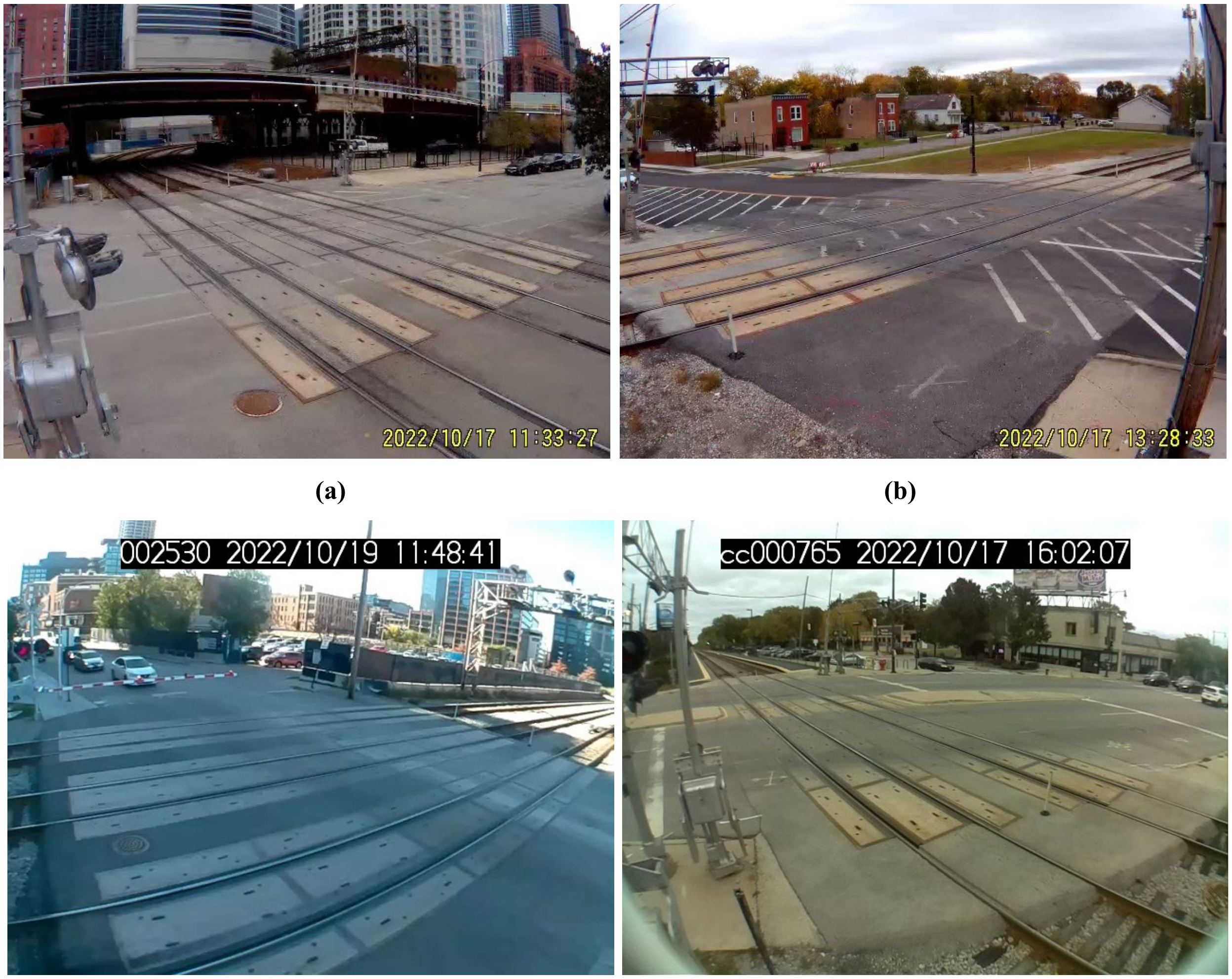
Views from the recorded locations can be seen in Figure 8 and Figure 9. Video data was recorded with the battery powered video recording system. The video was recorded at 640 x 480 pixels and 10 frames per second. The cameras were not equipped with infrared sensors to enhance nighttime detection; however, illumination was sufficient at all locations to enable reliable 24-hour detection.

(a)

(b)

(c)

Figure 8. Typical Views of Recorded Data from the (a) Connecticut Grade Crossing, (b) Louisiana Local Road Grade Crossing, (c) Louisiana Highway Grade Crossing



(a) **(b)**

(c) **(d)**

Figure 9. Typical Views of Recorded Data from the (a) Illinois Grade Crossing 1, (b) Illinois Grade Crossing 2, (c) Illinois Grade Crossing 3, and (d) Illinois Grade Crossing 4

5. Case Studies

The research team analyzed video data from 11 distinct locations across the United States. Two case study locations were selected for focused discussion and analysis: the New Jersey Grade Crossing and North Carolina ROW North View. The New Jersey grade crossing experiences a significant amount of train traffic, making it an ideal spot for monitoring and detecting trespass events. The second location is a stretch of ROW in North Carolina, which experiences large numbers of pedestrian trespass events. For this location, the stream was provided by Virtualrailfan, whose streaming service provides users with views of various railroad locations across the United States. Positioned along the ROW, this camera provided a live stream of the activities in the surrounding area.

5.1 New Jersey Commuter Rail Crossing Case Study

5.1.1 Location Description

This crossing is in New Jersey and abuts a train station which is shared by multiple rail lines running on two tracks. Three parking lots servicing the station surround the crossing. Two of the parking lots are west and one is east of the crossing. The area is in a downtown commercial district with shopping centers, schools, and restaurants nearby, as seen in Figure 10.

Figure 10. Satellite View of the New Jersey Grade Crossing

According to the latest U.S. Census estimates, the current population of the town where this crossing is located is 15,000. According to an FRA report (Bedini-Jacobini & DaSilva, 2020), three fatal pedestrian grade crossing accidents occurred at the selected study site in 2006, 2010, and 2016. Additionally, two vehicles that stopped at the crossing were struck by transit trains in

2010 and 2012 with no noted injuries or fatalities. Table 4 summarizes grade crossing incidents at the studied crossing.

Table 4. Summary of Historical Crossing Incidents (Bedini-Jacobini & DaSilva, 2020)

Date of Incident	Time	Type	Weather
6/9/2016	6:45 AM	Pedestrian Fatal	Clear
9/15/2012	12:00 PM	Stalled Empty Vehicle Struck, No Injuries	Clear
8/4/2010	7:43 AM	Pedestrian Fatal	Cloudy
5/21/2010	11:52 AM	Cement Truck Struck, No Injuries	Clear
2/1/2006	6:48 PM	Pedestrian Fatal	Clear

5.1.2 Data Collection and Validation

The system correctly identified 20,054 trespass events during the study period. A trespass event represents an occurrence that may consist of multiple trespassers within a single record or video clip. In the event dataset, information such as event type (e.g., car, pedestrian, truck, bus, bicycle), start and end date and time, event duration, trajectory, video link, weather, and temperature were stored. The weather information was obtained from OpenWeather API.

All records were manually reviewed and validated by the research team to ensure all trespass events were correctly identified. There are two types of errors, false positives (i.e., when the system reports a trespass event when none has occurred) and false negatives (i.e., when the system misses a trespass event), as seen in Table 5. When these errors were detected in the development period, the algorithm was modified and retested to ensure system accuracy.

Table 5. Error Types

	Rutgers AI System Detects a Trespass Event	Rutgers AI System Does Not Detect a Trespass Event
Trespass Event Occurs	True Positive	False Negative (Missed Detection)
No Trespass Event Occurs	False Positive (False Alarm)	True Negative

Initially, the prototype AI system identified 29,252 total events, of which 20,054 (~69 percent) were true and 9,198 (~31 percent) were false positives. False positive rates were then used to evaluate the system's performance. A false positive rate is the ratio of false positives to total detections. False positive rates began as high as 30 percent in this research and declined to as low as 8 percent as the software's parameters were adjusted and the AI was retrained. There were four main causes of false positives discovered in the trespass event dataset: false activation detections, duplicate detections, legal occupiers, and misclassifications. Examples of two types of false positives are shown in Figure 11.

Approximately 80 percent of the false positives were caused by false activation detections. False activations were caused by several contributing factors including inclement weather, headlight glare, and environmental conditions. These challenges were ameliorated through the adoption of more sophisticated activation detection algorithms. The initial algorithms simply checked the illumination levels of the signal light but recorded false activations when vehicle headlights shone on the signal lights. The final algorithm incorporates additional parameters to account for these conditions and checks for patterns in changing luminosity using a short-term Fourier Transform in addition to threshold parameters, resulting in improved performance.

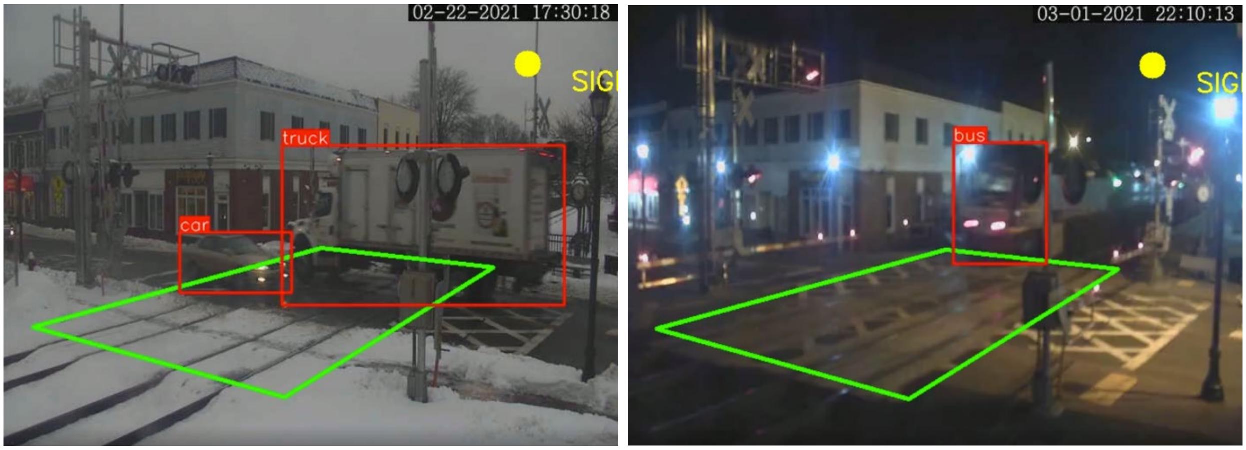


Figure 11. False Positives Due to (a) Obscured Signal and (b) Misclassification

Approximately 10 percent of false positives were caused by duplicate detections. These were caused by a loss of object tracking due to low frame rates and objects passing behind other objects. This was ameliorated by replacing the previously used Kalman filter tracking algorithms with the DeepSORT module. Approximately 5 percent of false positives were caused by legal occupiers. These included police officers and railroad workers present on the site during several grade crossing signal maintenance events over the study period. These would occur intermittently; however, 90 percent of legal occupier false positives occurred on July 18, 2022, during a single protracted maintenance event when police officers conducted traffic through the malfunctioning crossing. Approximately 5 percent of false positives were caused by misclassifications when the AI identified non-violating objects or video artifacts as violators. This issue was ameliorated by retraining the AI using annotated images from the dataset to increase detection confidence scores.

To detect missed detections, the team performed a series of 24-hour manual reviews of the system after deployment. During this analysis, the team members manually reviewed the raw video footage and identified all traffic, trespass events, train, and signal events. The AI system then analyzed the same footage and reported the results. The two datasets were compared to determine the system's relative accuracy.

False negative rates can be calculated by dividing the number of missed detections by the total number of actual trespass events. This analysis was performed three times during the study period: on February 10, 2021, June 14, 2021, and August 12, 2021. In each of these instances, no trespass events were missed by the system. While optimizing an AI system parameter, higher false positive or false negative rates can be favored as the system is improved. In this study, the parameter adjustments favored a lower false negative rate because false positives could be more easily identified and removed from the dataset.

5.1.3 Case Study Results

The team analyzed 20,054 grade crossing trespass events and visualized them from several perspectives, yielding weekly and hourly temporal heatmaps, trespass rates by trespasser type, monthly and seasonal trespass event trends, a near-miss analysis, and trespass event spatial analysis.

There were approximately 18 pedestrian trespass events and 60 vehicle trespass events per day, which differs from past studies (Zhang et al., 2022) conducted at this grade crossing. Past research by Zhang et al. (2022) showed 158 pedestrian trespass events and seventy-four vehicle trespass events per day in 2018 and 2019. Comparatively, the current report encompasses a year of trespass events across four seasons, yielding a more comprehensive temporal and categorical analysis. Past research may have encountered weeks when trespass event rates were higher or lower than the long-term average. Past data was also collected before the COVID-19 pandemic, which may have had additional effects on pedestrian and vehicle traffic volumes.

5.1.3.1 Trespass Event Temporal Heatmap

Heatmaps of trespass events for cars, pedestrians, trucks, bicycles, buses, and total trespass events across one-hour intervals for each day of the week are shown in Figure 12. Approximately 11.2 percent of all trespass events occurred between 7 P.M. and 8 P.M., which is the one-hour window with the highest percentage of trespass events. Car trespass events accounted for 69 percent and pedestrian trespass events for 23 percent of all trespass events. These findings are partially consistent with previous preliminary research conducted at this grade crossing (Zhang et al., 2022), with the exception that past research showed higher counts of trespass events on weekends than on weekdays.

Figure 12 shows two temporal hot spots on weekdays from 5 P.M. to 8 P.M. and from 6 A.M. to 8 A.M. These are consistent with typical commuter rush hours. Two main parking lots are on the west side of the tracks, and New York-bound trains run on the west track of this two-track line. During the morning commute, most people board the train from the same side and do not need to traverse the crossing. However, commuters returning in the evening may need to traverse the crossing to reach the parking lots. This behavior may explain the higher frequency of the afternoon trespass events compared to the morning rush hour. This observation holds true for both car and pedestrian trespass events. Rush hour car trespass events comprise 17 percent (morning) and 40 percent (evening) of all car trespass events. Rush hour pedestrian trespass events comprise 13 percent (morning) and 42 percent (evening) of all pedestrian trespass events.

This pattern was not observed for trucks, bicycles, or buses, which further reinforces the commuter trespass events hypothesis. Regarding trucks, one assumption is that many truck drivers drive earlier in the day to avoid peak traffic on the road. Figure 12(c) shows a temporal hotspot within the 6 A.M. to 8 A.M. interval.

During the study period, 6,962 trespass events occurred during the commute hours from 5 P.M. to 8 P.M. This represents approximately 35 percent of all trespass events occurring during only 17 percent of the hours of the week. Identifying the evening commute temporal hotspot can aid in the efficient deployment of railroad police to ameliorate trespass events during this time slot. Vehicle trespass events could be further reduced with the implementation of a photo enforcement system and/or targeted high visibility traffic signs (Ngamdung & DaSilva, 2019).

	Hour of Day																								
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Grand Total
Monday	28	9	4	0	7	47	109	132	99	58	30	45	51	59	46	96	113	168	160	221	236	57	56	34	1,865
Tuesday	27	15	4	0	10	89	131	131	139	65	24	53	42	69	67	123	131	219	184	266	285	75	60	29	2,238
Wednesday	28	22	8	0	10	63	144	146	183	94	31	44	66	65	39	115	137	229	194	291	263	72	76	25	2,345
Thursday	29	21	8	1	7	77	135	121	185	107	50	62	69	70	73	127	148	256	220	268	265	91	52	40	2,482
Friday	27	21	9	0	4	77	112	103	138	76	38	43	48	52	60	117	135	237	218	290	265	84	53	34	2,241
Saturday	37	39	10	0	2	16	41	76	77	26	48	19	35	61	49	19	92	84	106	109	80	32	93	40	1,191
Sunday	39	34	9	3	0	7	33	63	69	26	35	22	35	31	52	17	79	65	110	124	93	23	76	23	1,068
Grand Total	215	161	52	4	40	376	705	772	890	452	256	288	346	407	386	614	835	1,258	1,192	1,569	1,487	434	466	225	13,430

(a) Car Trespass Events

	Hour of Day																								
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Grand Total
Monday	3	2	2	0	0	12	36	27	37	15	14	17	28	20	31	47	40	99	70	76	63	17	10	5	671
Tuesday	5	2	0	1	1	6	34	39	31	16	11	12	15	28	22	54	40	94	90	102	50	29	16	12	710
Wednesday	2	4	1	0	0	15	32	42	54	21	14	10	18	34	37	58	66	91	112	90	70	19	12	11	813
Thursday	3	5	2	3	4	13	34	32	44	19	13	28	21	31	27	56	71	127	85	84	67	28	17	13	827
Friday	2	2	4	1	1	9	24	31	37	22	10	23	17	35	30	53	48	99	88	95	61	27	18	14	751
Saturday	6	10	2	0	0	0	2	16	22	8	20	3	19	21	34	9	43	32	36	39	25	6	35	19	407
Sunday	19	6	7	0	0	2	6	17	27	23	23	15	28	24	36	10	38	29	30	31	34	7	17	3	432
Grand Total	40	31	18	5	6	57	168	204	252	124	105	108	146	193	217	287	346	571	511	517	370	133	125	77	4,611

(b) Pedestrian Trespass Events

	Hour of Day																								
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Grand Total
Monday	0	0	0	0	0	4	29	26	25	16	5	13	7	11	4	15	13	17	19	20	14	3	3	3	247
Tuesday	2	0	0	1	0	7	40	43	16	19	8	9	14	18	7	14	11	21	11	32	17	5	2	3	300
Wednesday	0	0	1	0	1	8	34	35	25	14	13	12	12	16	17	18	21	24	17	20	18	0	4	2	312
Thursday	1	0	1	1	0	7	25	30	28	16	11	13	12	11	19	17	18	30	31	21	15	4	3	2	316
Friday	1	4	2	0	0	7	41	34	19	19	9	11	8	10	5	16	23	24	32	25	7	3	2	0	302
Saturday	1	1	0	0	0	5	13	29	13	13	17	3	13	9	14	1	17	8	3	8	1	0	1	0	170
Sunday	0	0	1	0	0	3	4	11	8	5	1	3	3	1	7	2	13	5	7	11	3	2	4	1	95
Grand Total	5	5	5	2	1	41	186	208	134	102	64	64	69	76	73	83	116	129	120	137	75	17	19	11	1,742

(c) Truck Trespass Events

	Hour of Day																								
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Grand Total
Monday	0	0	0	0	0	1	0	0	4	1	0	1	1	3	0	5	2	4	4	4	6	1	0	0	37
Tuesday	0	0	0	0	0	0	2	1	0	1	0	1	1	2	3	9	5	6	8	6	3	1	0	0	49
Wednesday	0	0	0	0	0	2	1	0	2	0	1	1	0	3	3	4	5	2	6	5	1	2	1	1	40
Thursday	0	0	0	0	0	2	0	0	5	1	0	0	1	1	4	4	3	8	11	4	4	1	0	0	49
Friday	0	0	0	0	0	0	3	3	2	1	1	0	1	2	2	7	3	5	2	5	3	3	0	0	43
Saturday	0	0	0	0	0	0	0	1	0	0	0	0	1	1	5	1	3	4	3	2	1	1	3	0	26
Sunday	0	0	0	0	0	0	0	0	4	2	2	0	3	1	1	0	4	1	2	2	0	0	0	1	23
Grand Total	0	0	0	0	0	5	6	5	17	6	4	3	8	13	18	30	25	30	36	28	18	9	4	2	267

(d) Bicycle Trespass Events

	Hour of Day																								
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Grand Total
Monday	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Tuesday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Wednesday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Thursday	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Friday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
Saturday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sunday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grand Total	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	4

(e) Bus Trespass Events

	Hour of Day																								
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Grand Total
Monday	31	11	6	0	7	64	174	186	165	90	49	76	87	93	81	163	168	288	253	321	319	78	69	42	2,821
Tuesday	34	17	4	2	11	102	207	214	186	101	43	75	72	117	99	200	187	340	293	406	356	110	78	44	3,298
Wednesday	30	26	10	0	11	88	211	223	264	129	59	67	96	118	96	195	229	346	329	406	352	93	93	39	3,510
Thursday	33	26	11	5	11	99	194	184	262	143	74	103	103	113	123	204	240	421	347	377	351	124	72	55	3,675
Friday	30	27	15	1	5	93	180	171	196	118	58	77	74	99	97	193	209	365	341	415	336	117	73	48	3,338
Saturday	44	50	12	0	2	21	56	122	112	47	85	25	68	92	102	30	155	128	148	158	107	39	132	59	1,794
Sunday	58	40	17	3	0	12	43	91	108	56	61	40	69	57	96	29	134	100	149	168	130	32	97	28	1,618
Grand Total	260	197	75	11	47	479	1,065	1,191	1,293	684	429	463	569	689	694	1,014	1,322	1,988	1,860	2,251	1,951	593	614	315	20,054

(f) Total Trespass Events

Figure 12. Trespass Event Heatmaps by Time and Day: (a) Cars; (b) Pedestrians; (c) Trucks; (d) Bicycles; (e) Buses; and (f) Total Trespass Events (January 1, 2021, to January 31, 2022)

5.1.3.2 Trespass Events Rates by Class

Table 6 shows the factor analysis of five distinct types of trespass events. During the study period, the total car, pedestrian, truck, bicycle, and bus traffic was collected, and the average daily traffic was calculated by class.

In Table 6, daily car traffic is significantly larger than traffic from pedestrians, trucks, bicycles, and buses. This table shows the exposure rate of violators by classification as the rate of traffic per thousand. Pedestrians have the highest trespass event rate amongst all classes, indicating that this class is the least compliant and may be targeted for mitigation strategies. Buses are the most compliant class and have the lowest trespass event rate of all classes. This may be due to specific training that bus drivers receive to stop and proceed at grade crossings.

Table 6. Factor Analysis of Trespass Events by Class (January 1, 2021, to January 31, 2022)

Class	Total Traffic	Total Trespass Events	Object Class Based Average Daily Traffic	Average Trespass Events Per Day	Trespass Event Rate Per Thousand
Car	3,160,317	13,430	12,103	52.87	4.25
Pedestrian	550,506	4,611	2,099	18.15	8.38
Truck	487,678	1,742	1,868	6.89	3.57
Bicycle	56,583	267	217	1.05	4.72
Bus	3,108	4	12	0.02	1.29
Total	4,258,192	20,054	16,299	78.98	4.71

5.1.3.3 Trespass Event Rates by Class Normalized by Traffic

Figure 13 shows weekly and hourly temporal heatmaps of the trespass event rate per thousand for cars, pedestrians, trucks, bicycles, buses, and total trespass events across one-hour intervals for each day of the week. The trespass event rate per thousand is obtained by dividing the number of trespass events in each timeslot by the number of corresponding traffic and multiplying by 1,000.

Figure 12 (above) shows that more trespass events occurred during evening rush hours. However, when normalized against traffic, grade crossing users are shown to be less compliant during the morning rush hours from 6 A.M. to 8 A.M. Figure 13 indicates that even though more trespass events occur during the afternoon commute, all classes are less compliant in the morning hours. This insight may help to focus enforcement solutions on effectively mitigating trespass events during the least compliant hours. Additionally, a difference in trespass event rate per thousand can be seen between weekdays and weekends. This finding could lead to more effective time-targeted law enforcement efforts.

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	2.67	3.37	1.51	0.91	0.00	9.68	82.09	184.75	102.22	12.30	5.99	1.55	1.72	1.71	2.85	0.77	2.86	2.16	3.26	3.72	2.75	0.67	2.35	0.87
Tuesday	1.48	0.67	0.54	0.00	4.13	63.86	243.85	292.04	110.86	22.95	4.44	2.65	2.06	2.82	2.25	3.54	3.04	4.35	4.10	5.40	5.61	1.34	1.38	1.09
Wednesday	1.12	0.95	0.46	0.00	5.39	106.08	239.05	290.47	155.66	21.88	3.12	2.71	1.53	2.88	2.87	4.19	3.59	5.54	4.76	6.75	6.97	1.79	1.51	0.91
Thursday	1.25	1.36	0.89	0.00	4.98	69.31	260.87	272.39	212.79	38.09	5.13	3.00	2.68	2.94	1.75	4.10	4.02	6.36	5.20	7.16	6.35	1.72	1.89	0.79
Friday	1.22	1.23	0.77	0.17	2.38	37.54	100.15	178.99	208.10	47.28	8.86	4.26	3.18	3.56	3.53	5.27	4.94	7.63	6.41	7.25	6.57	2.23	1.30	1.18
Saturday	1.05	1.08	0.62	0.00	0.74	22.61	56.74	112.45	167.27	42.58	9.07	4.59	2.73	2.42	2.19	3.38	3.51	6.23	5.92	7.90	7.64	2.58	1.67	1.23
Sunday	1.61	2.32	0.80	0.00	0.37	5.25	23.95	89.83	130.07	23.99	17.70	3.06	3.26	3.41	2.14	0.67	3.00	2.75	3.70	4.00	3.22	1.34	4.12	2.04

(a) Car Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	1.73	1.51	1.69	0.00	0.00	169.01	378.95	300.00	303.28	33.26	10.73	9.24	13.03	8.39	8.36	9.96	8.72	17.11	10.59	11.18	10.53	3.12	1.99	1.27
Tuesday	1.97	1.04	0.00	2.16	6.45	73.17	425.00	300.00	212.33	31.62	6.74	4.85	6.57	13.13	6.90	13.26	6.83	12.31	12.69	14.24	6.84	4.24	2.41	2.40
Wednesday	0.63	1.60	0.79	0.00	0.00	161.29	711.11	328.13	339.62	47.62	7.61	3.64	6.50	13.92	11.93	12.82	11.28	11.87	16.14	12.54	10.73	2.95	1.95	2.47
Thursday	1.11	2.52	1.63	4.57	16.81	173.33	382.02	344.09	369.75	45.56	10.86	13.37	8.28	12.02	9.02	13.95	12.22	19.84	13.26	13.37	10.51	4.86	3.17	3.53
Friday	0.81	1.03	2.89	1.47	2.39	19.69	66.85	303.92	342.59	55.84	7.38	11.27	8.31	16.39	9.95	16.20	9.76	12.62	12.40	14.28	9.20	4.53	3.19	2.77
Saturday	1.64	4.25	1.00	0.00	0.00	0.00	3.77	128.00	194.69	31.62	13.90	1.20	5.67	5.67	6.30	1.48	5.78	3.80	4.43	5.21	3.70	1.05	7.26	4.36
Sunday	5.92	2.81	4.09	0.00	0.00	3.21	12.42	171.72	221.31	79.04	23.19	8.19	9.24	4.16	3.55	0.74	2.50	2.53	4.20	5.43	6.34	1.58	4.52	1.01

(b) Pedestrian Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	0.00	0.00	0.00	0.00	0.00	153.85	604.17	366.20	316.46	61.78	3.38	3.32	1.46	2.32	0.76	2.59	2.11	2.81	3.04	3.53	2.49	0.62	0.73	1.22
Tuesday	2.11	0.00	0.00	12.99	0.00	162.79	540.54	413.46	160.00	57.40	4.62	1.86	2.45	3.19	1.15	1.89	1.30	2.70	1.56	4.55	2.53	0.90	0.44	1.26
Wednesday	0.00	0.00	6.71	0.00	22.73	275.86	576.27	353.54	403.23	47.95	7.01	2.46	1.91	2.71	2.58	2.33	2.52	3.12	2.33	2.95	2.70	0.00	0.92	0.79
Thursday	0.96	0.00	6.99	16.95	0.00	218.75	595.24	394.74	288.66	72.40	8.01	3.33	2.23	1.98	3.26	2.40	2.37	4.11	4.49	3.05	2.37	0.73	0.69	0.83
Friday	1.02	11.49	9.71	0.00	0.00	107.69	422.68	309.09	231.71	72.52	6.40	2.96	1.73	2.00	0.90	2.59	3.36	3.67	5.12	4.00	1.20	0.57	0.48	0.00
Saturday	1.01	3.02	0.00	0.00	0.00	98.04	433.33	475.41	152.94	42.35	15.71	1.17	3.22	1.90	2.49	0.15	2.60	1.44	0.59	1.73	0.25	0.00	0.32	0.00
Sunday	0.00	0.00	5.35	0.00	0.00	57.69	100.00	255.81	205.13	35.97	2.12	2.69	1.49	0.37	2.01	0.51	3.39	1.42	1.83	3.34	1.06	0.75	1.78	0.68

(c) Truck Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	0.00	0.00	0.00	0.00	0.00	1,000.00	0.00	0.00	250.00	142.86	0.00	7.46	4.76	18.99	0.00	15.53	4.87	6.92	5.25	4.12	6.55	1.49	0.00	0.00
Tuesday	0.00	0.00	0.00	0.00	0.00	0.00	1,000.00	1,000.00	0.00	58.82	0.00	5.56	4.20	10.87	12.35	24.73	10.02	8.31	9.90	6.45	2.62	1.04	0.00	0.00
Wednesday	0.00	0.00	0.00	0.00	0.00	1,000.00	1,000.00	0.00	133.33	0.00	7.35	3.83	0.00	15.08	10.64	9.37	10.71	2.21	6.53	4.56	0.99	2.38	1.32	2.19
Thursday	0.00	0.00	0.00	0.00	0.00	285.71	0.00	0.00	238.10	166.67	0.00	0.00	4.61	4.57	17.70	11.83	10.00	13.86	16.79	4.27	4.93	1.48	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	1,000.00	750.00	117.65	52.63	12.50	0.00	4.83	14.93	7.94	23.97	8.04	9.06	2.61	5.75	3.65	3.87	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	333.33	0.00	0.00	0.00	0.00	2.62	2.72	9.40	1.35	4.34	4.99	3.38	2.31	1.03	1.16	5.38	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	105.26	117.65	19.42	0.00	6.67	2.11	1.82	0.00	5.24	1.13	2.42	2.16	0.00	0.00	0.00	3.14

(d) Bicycle Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1,000.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tuesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	35.71	0.00	0.00	0.00
Wednesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	250.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	14.29	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(e) Bus Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	1.82	0.94	0.82	0.00	3.85	74.16	280.19	324.04	178.96	31.45	5.57	3.76	3.15	3.65	2.94	4.94	4.32	6.74	5.32	6.82	6.85	1.72	1.64	1.27
Tuesday	1.50	1.08	0.44	0.45	5.78	111.72	330.14	311.95	156.30	29.79	4.16	3.05	2.17	4.05	3.30	5.12	3.59	6.20	5.41	7.22	6.20	1.97	1.48	1.12
Wednesday	1.04	1.38	0.97	0.00	5.18	93.82	316.34	318.57	224.68	34.33	5.09	2.43	2.60	3.63	2.88	4.63	4.47	6.18	6.10	7.44	6.38	1.70	1.82	0.99
Thursday	1.25	1.39	1.05	0.92	4.80	95.38	287.41	267.05	237.53	45.75	8.40	4.92	3.13	3.70	3.92	5.16	5.01	8.35	6.75	6.87	6.38	2.30	1.42	1.44
Friday	1.10	1.38	1.23	0.15	1.46	36.09	100.73	195.43	186.84	40.58	6.81	3.75	2.59	3.67	3.29	5.70	4.96	7.52	7.02	8.15	6.26	2.22	1.45	1.14
Saturday	1.43	2.24	0.70	0.00	0.31	4.82	22.70	112.44	113.13	20.37	12.35	1.69	2.68	3.03	2.61	0.62	2.91	2.42	2.90	3.18	2.31	0.91	3.27	1.73
Sunday	2.14	2.07	1.16	0.30	0.00	3.22	19.13	91.73	137.93	36.58	14.29	4.27	4.24	2.12	2.59	0.62	2.65	2.15	3.68	4.51	3.81	1.01	3.34	1.15

(f) Total Trespass Events

Figure 13. Trespass Event Rate Per Thousand Heatmaps by Time and Day: (a) Cars; (b) Pedestrians; (c) Trucks; (d) Bicycles; (e) Buses; and (f) Total Trespass Events (January 1, 2021, to January 31, 2022).

5.1.3.4 Trespass Event Rates by Class Normalized by Signal Activations

Figure 14 shows a temporal heatmap of the total number of signals for each hour of the day and day of the week in the study period. There was a total of 20,020 signal activations during the study period and 4,957 (25 percent) of them occurred on weekdays between 5 P.M. and 8 P.M.

	Hour of Day																								
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Grand Total
Monday	106	71	47	30	31	105	120	109	133	94	64	86	102	100	107	161	155	225	199	224	266	140	129	74	2,878
Tuesday	93	104	76	26	61	126	147	137	174	120	80	105	123	141	116	184	178	282	236	259	287	162	106	85	3,408
Wednesday	87	137	71	42	42	140	157	161	189	124	103	91	117	129	119	207	197	247	204	256	278	139	123	68	3,428
Thursday	89	101	62	21	48	121	155	127	187	151	104	104	115	116	111	170	185	286	213	239	275	146	115	86	3,327
Friday	89	124	81	10	38	134	143	121	142	120	73	105	112	114	104	183	176	245	213	247	276	169	104	69	3,192
Saturday	98	136	64	8	6	46	72	88	84	54	78	38	84	72	127	34	121	90	112	124	99	74	190	71	1,970
Sunday	129	80	63	9	3	27	53	74	92	57	63	27	75	60	95	35	142	84	106	114	108	86	164	71	1,817
Grand Total	691	753	464	146	229	699	847	817	1,001	720	565	556	728	732	779	974	1,154	1,459	1,283	1,463	1,589	916	931	524	20,020

Figure 14. Grade Crossing Activations (January 1, 2021, to January 31, 2022)

Figure 15 shows weekly and hourly temporal heatmaps of the trespass event rate per signal activation for cars, pedestrians, trucks, bicycles, buses, and total trespass events across one-hour intervals for each day of the week. The trespass event rate per signal activation is obtained by dividing the number of trespass events by the number of signal activations in each one-hour interval.

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	0.26	0.13	0.09	0.00	0.23	0.45	0.91	1.21	0.74	0.62	0.47	0.52	0.50	0.59	0.43	0.60	0.73	0.75	0.80	0.99	0.89	0.41	0.43	0.46
Tuesday	0.29	0.14	0.05	0.00	0.16	0.71	0.89	0.96	0.80	0.54	0.30	0.50	0.34	0.49	0.58	0.67	0.74	0.78	0.78	1.03	0.99	0.46	0.57	0.34
Wednesday	0.32	0.16	0.11	0.00	0.24	0.45	0.92	0.91	0.97	0.76	0.30	0.48	0.56	0.50	0.33	0.56	0.70	0.93	0.95	1.14	0.95	0.52	0.62	0.37
Thursday	0.33	0.21	0.13	0.05	0.15	0.64	0.87	0.95	0.99	0.71	0.48	0.60	0.60	0.60	0.66	0.75	0.80	0.90	1.03	1.12	0.96	0.62	0.45	0.47
Friday	0.30	0.17	0.11	0.00	0.11	0.57	0.78	0.85	0.97	0.63	0.52	0.41	0.43	0.46	0.58	0.64	0.77	0.97	1.02	1.17	0.96	0.50	0.51	0.49
Saturday	0.38	0.29	0.16	0.00	0.33	0.35	0.57	0.86	0.92	0.48	0.62	0.50	0.42	0.85	0.39	0.56	0.76	0.93	0.95	0.88	0.81	0.43	0.49	0.56
Sunday	0.30	0.43	0.14	0.33	0.00	0.26	0.62	0.85	0.75	0.46	0.56	0.81	0.47	0.52	0.55	0.49	0.56	0.77	1.04	1.09	0.86	0.27	0.46	0.32

(a) Car Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	0.03	0.03	0.04	0.00	0.00	0.11	0.30	0.25	0.28	0.16	0.22	0.20	0.27	0.20	0.29	0.29	0.26	0.44	0.35	0.34	0.24	0.12	0.08	0.07
Tuesday	0.05	0.02	0.00	0.04	0.02	0.05	0.23	0.28	0.18	0.13	0.14	0.11	0.12	0.20	0.19	0.29	0.22	0.33	0.38	0.39	0.17	0.18	0.15	0.14
Wednesday	0.02	0.03	0.01	0.00	0.00	0.11	0.20	0.26	0.29	0.17	0.14	0.11	0.15	0.26	0.31	0.28	0.34	0.37	0.55	0.35	0.25	0.14	0.10	0.16
Thursday	0.03	0.05	0.03	0.14	0.08	0.11	0.22	0.25	0.24	0.13	0.13	0.27	0.18	0.27	0.24	0.33	0.38	0.44	0.40	0.35	0.24	0.19	0.15	0.15
Friday	0.02	0.02	0.05	0.10	0.03	0.07	0.17	0.26	0.26	0.18	0.14	0.22	0.15	0.31	0.29	0.29	0.27	0.40	0.41	0.38	0.22	0.16	0.17	0.20
Saturday	0.06	0.07	0.03	0.00	0.00	0.00	0.03	0.18	0.26	0.15	0.26	0.08	0.23	0.29	0.27	0.26	0.36	0.36	0.32	0.31	0.25	0.08	0.18	0.27
Sunday	0.15	0.08	0.11	0.00	0.00	0.07	0.11	0.23	0.29	0.40	0.37	0.56	0.37	0.40	0.38	0.29	0.27	0.35	0.28	0.27	0.31	0.08	0.10	0.04

(b) Pedestrian Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	0.00	0.00	0.00	0.00	0.00	0.04	0.24	0.24	0.19	0.17	0.08	0.15	0.07	0.11	0.04	0.09	0.08	0.08	0.10	0.09	0.05	0.02	0.02	0.04
Tuesday	0.02	0.00	0.00	0.04	0.00	0.06	0.27	0.31	0.09	0.16	0.10	0.09	0.11	0.13	0.06	0.08	0.06	0.07	0.05	0.12	0.06	0.03	0.02	0.04
Wednesday	0.00	0.00	0.01	0.00	0.02	0.06	0.22	0.22	0.13	0.11	0.13	0.13	0.10	0.12	0.14	0.09	0.11	0.10	0.08	0.08	0.06	0.00	0.03	0.03
Thursday	0.01	0.00	0.02	0.05	0.00	0.06	0.16	0.24	0.15	0.11	0.11	0.13	0.10	0.09	0.17	0.10	0.10	0.10	0.15	0.09	0.05	0.03	0.03	0.02
Friday	0.01	0.03	0.02	0.00	0.00	0.05	0.29	0.28	0.13	0.16	0.12	0.10	0.07	0.09	0.05	0.09	0.13	0.10	0.15	0.10	0.03	0.02	0.02	0.00
Saturday	0.01	0.01	0.00	0.00	0.00	0.11	0.18	0.33	0.15	0.24	0.22	0.08	0.15	0.13	0.11	0.03	0.14	0.09	0.03	0.06	0.01	0.00	0.01	0.00
Sunday	0.00	0.00	0.02	0.00	0.00	0.11	0.08	0.15	0.09	0.09	0.02	0.11	0.04	0.02	0.07	0.06	0.09	0.06	0.07	0.10	0.03	0.02	0.02	0.01

(c) Truck Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.03	0.01	0.00	0.01	0.01	0.03	0.00	0.03	0.01	0.02	0.02	0.02	0.02	0.01	0.00	0.00
Tuesday	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.03	0.05	0.03	0.02	0.03	0.02	0.01	0.01	0.00	0.00
Wednesday	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.00	0.02	0.03	0.02	0.03	0.01	0.03	0.02	0.00	0.01	0.01	0.01
Thursday	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.03	0.01	0.00	0.00	0.01	0.01	0.04	0.02	0.02	0.03	0.05	0.02	0.01	0.01	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.01	0.01	0.01	0.00	0.01	0.02	0.02	0.04	0.02	0.02	0.01	0.02	0.01	0.02	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.04	0.03	0.02	0.04	0.03	0.02	0.01	0.01	0.02	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.04	0.03	0.00	0.04	0.02	0.01	0.00	0.03	0.01	0.02	0.02	0.00	0.00	0.00	0.01

(d) Bicycle Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tuesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wednesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(e) Bus Trespass Events

	Hour of Day																							
Day of Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	0.29	0.15	0.13	0.00	0.23	0.61	1.45	1.71	1.24	0.96	0.77	0.88	0.85	0.93	0.76	1.01	1.08	1.28	1.27	1.43	1.20	0.56	0.53	0.57
Tuesday	0.37	0.16	0.05	0.08	0.18	0.81	1.41	1.56	1.07	0.84	0.54	0.71	0.59	0.83	0.85	1.09	1.05	1.21	1.24	1.57	1.24	0.68	0.74	0.52
Wednesday	0.34	0.19	0.14	0.00	0.26	0.63	1.34	1.39	1.40	1.04	0.57	0.74	0.82	0.91	0.81	0.94	1.16	1.40	1.61	1.59	1.27	0.67	0.76	0.57
Thursday	0.37	0.26	0.18	0.24	0.23	0.82	1.25	1.45	1.40	0.95	0.71	0.99	0.90	0.97	1.11	1.20	1.30	1.47	1.63	1.58	1.28	0.85	0.63	0.64
Friday	0.34	0.22	0.19	0.10	0.13	0.69	1.26	1.41	1.38	0.98	0.79	0.73	0.66	0.87	0.93	1.05	1.19	1.49	1.60	1.68	1.22	0.69	0.70	0.70
Saturday	0.45	0.37	0.19	0.00	0.33	0.46	0.78	1.39	1.33	0.87	1.09	0.66	0.81	1.28	0.80	0.88	1.28	1.42	1.32	1.27	1.08	0.53	0.69	0.83
Sunday	0.45	0.50	0.27	0.33	0.00	0.44	0.81	1.23	1.17	0.98	0.97	1.48	0.92	0.95	1.01	0.83	0.94	1.19	1.41	1.47	1.20	0.37	0.59	0.39

(f) Total Trespass Events

Figure 15. Trespass Events Per Signal Light Heatmaps by Time and Day: (a) Cars; (b) Pedestrians; (c) Trucks; (d) Bicycles; (e) Buses; and (f) Total Trespass Events (January 1, 2021, to January 31, 2022).

Total trespass events per signal activation share a similar temporal intensity pattern as total trespass events but differ when compared to trespass event rates per thousand pedestrian and vehicle traffic. The graphic shows higher trespass event rates per signal during the morning weekday rush hours of 6 A.M. – 8 A.M. and evening rush hours of 5 P.M. – 8 P.M. These intervals also experience a high number of signal activations, which increases the opportunities for trespass events to occur.

Car trespass events per signal activation show a change in temporal intensity compared to the total car trespass event rates and car trespass event rate per thousand. Car trespass event rates per signal activation are highest on Mondays at 7 A.M. and all days of the week between 5 P.M. and 8 P.M. Pedestrian trespass events per signal activation show a change in temporal intensity compared to total pedestrian trespass events and pedestrian trespass event rates per thousand. The highest pedestrian trespass event rates per signal activation are on Wednesdays at 6 P.M. and Sundays at 11 A.M. The presence of emergent one-hour hotspots provides an opportunity for targeted enforcement to address the hours with the worst compliance.

Truck trespass events per signal activation show a similar trend in temporal intensity compared to total truck trespass events and truck trespass event rates per thousand. In each of the heatmaps, the hours of 6 A.M. – 8 A.M. have the highest counts, rates per thousand, and rates per signal activation, indicating a converging trend of noncompliance during these hours. An education or enforcement campaign targeted at trucks during this interval could be maximally effective.

Bicycle trespass events per signal activation have a similar temporal intensity compared to total bicycle trespass events but differ from bicycle trespass event rates per thousand. Recommendations based on the total bicycle trespass events would remain the same following this analysis. Similarly, bus trespass event rates per signal activation show similar temporal intensities when compared to total bus trespass events and bus trespass event rates per thousand. However, the number of bus trespass events in the sample is small, so more data is required to ascertain trends and develop recommendations.

5.1.3.5 Trespass Events Near-miss Analysis

In this research a near-miss trespass event is defined as a trespass event that occurs after the signals have activated but before the train has arrived, indicating a potential collision with the train. Researchers found that 4,295 trespass events occurred before the train arrived, comprising 21 percent of the total dataset. The near-miss time was obtained by subtracting the nearest time of train arrival from the time of the trespass event before the train arrived.

During the study period, 20,020 signal activations were observed. Of those activations, there were 10,740 where no train was detected, 9,180 where one train was detected, and 100 signals where two trains were detected, as shown in Figure 16. The 10,740 events with no trains detected can be explained by the crossing's proximity to a rail station. In these scenarios, a train will approach the station, triggering the signals. The train stops at the station before proceeding through the crossing, causing the signals to deactivate. When the train begins to depart the station, the signals will reactivate, and the train will be detected traversing the crossing.

The near-miss analyses of the trespass events for cars, pedestrians, trucks, bicycles, buses, and total trespass events are shown in Figure 17. In this figure, each dot represents the total number of trespass events that occurred at specific near-miss times. In practice, near-misses are identified subjectively as observed by locomotive engineers and safety officials and may have durations as short as 5-10 seconds. In Figure 17, the team chose 45 seconds between the train and trespass event as the cutoff to illustrate the different patterns between classes.

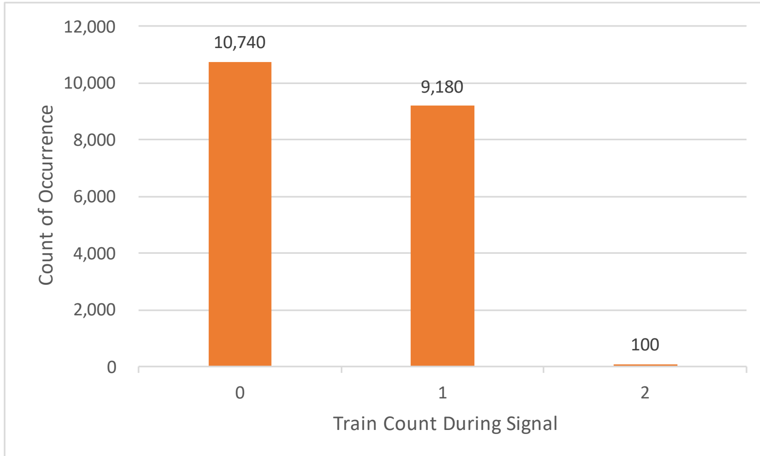
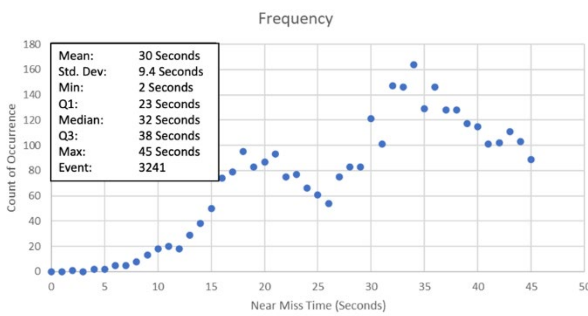
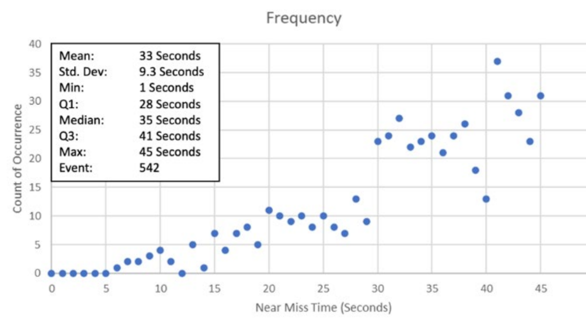


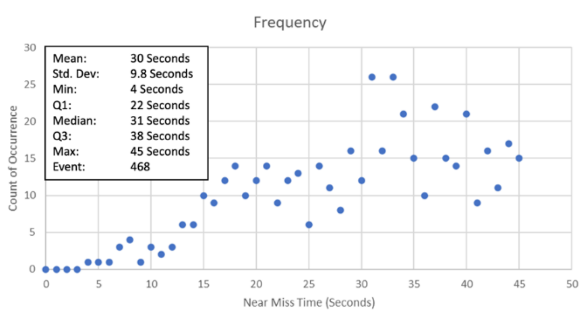
Figure 16. Train Counts During Signals from January 1, 2021, to January 31, 2022



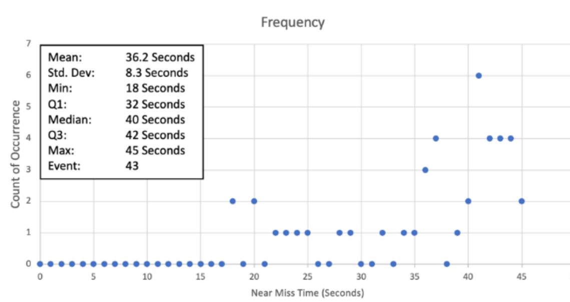
(a) Car



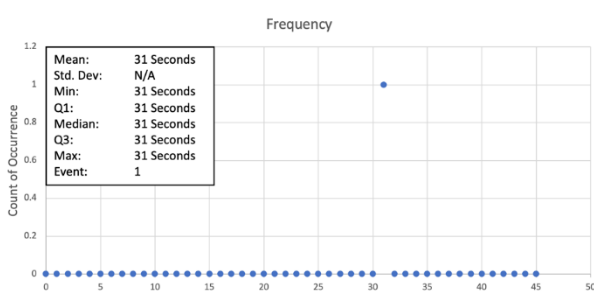
(b) Pedestrian



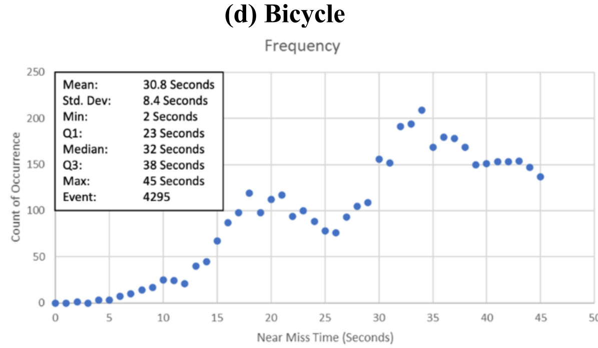
(c) Truck



(d) Bicycle



(e) Bus



(f) All Trespass Events

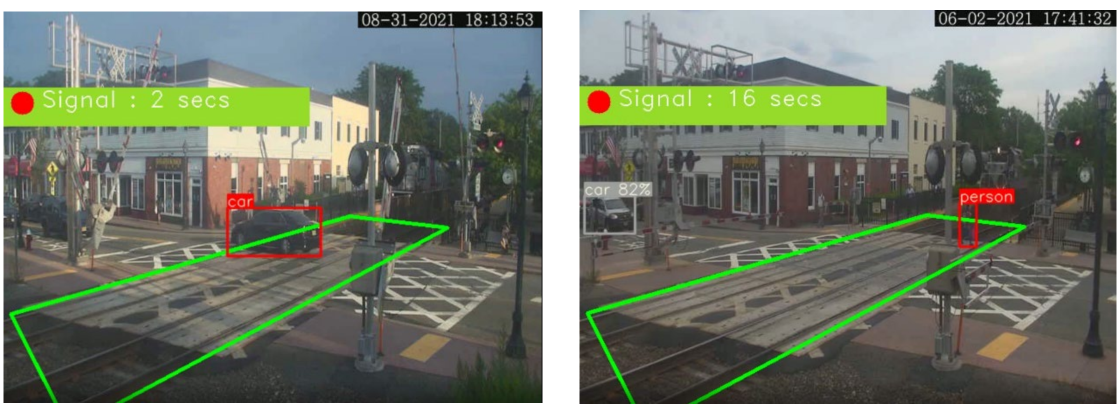
Figure 17. New Jersey Grade Crossing Near-Miss Distribution for (a) Car, (b) Pedestrian, (c) Truck, (d) Bicycle, (e) Bus, and (f) All Trespass Events (January 1, 2021, to January 31, 2022)

The near-miss distribution of all types of trespass events indicates an average near-miss time of 30.8 seconds. Eighty-one percent of trespass events occurred within 20 to 40 seconds of the train's arrival. About 1 percent of trespass events occurred within less than 10 seconds of the train's arrival, representing an extremely dangerous scenario.

In the distribution for car trespass events, two peaks were observed, centered around 20 seconds and 35 seconds. The crossing is adjacent to a nearby station and activates when a train approaches the station. If the train stops at the station, the crossing will deactivate without the train having passed. After passengers have boarded and disembarked from the train, the train will proceed, and the crossing will activate again. Trespass events during the first activation were likely to occur approximately 35 seconds before the train arrived, while trespass events during the second of these activations were centered around the 20-second peak.

Most trespass events occurred within 20 to 40 seconds, and the average near-miss time was about 30 seconds for the grade crossing car and truck near-miss distributions. The average near-miss times for pedestrians and bicycles were 33 seconds and 36.2 seconds, respectively. The speed difference between motor vehicles and pedestrians/bicycles may have caused this average difference in near-miss times, but this conclusion requires more evidence.

Examples of trespass events that occurred within 10 seconds can be seen in Figure 18. In Figure 18(a), the car entered the grade crossing when the gate was lowering, and the train entered the ROI from the station within 10 seconds. In Figure 18(b), the pedestrian entered the grade crossing when the gate was fully horizontal, and the train entered the ROI within 10 seconds. Both situations were extremely dangerous for the trespassers and should be given the utmost attention when developing mitigation strategies.



(a) (b)

Figure 18. (a) New Jersey Grade Crossing Car and (b) Pedestrian Trespass Event that Occurred Within 10 Seconds of a Train's Arrival

5.1.3.6 Trespass Event Spatial Heatmap Analysis

This research captured spatial information about trespass events using the DeepSORT module, which recorded the path of each trespass event. In Figure 19, 20,054 trajectories are visualized into 4 zones. This trajectory information reveals the flow of trespass events and leads to suggested potential actions to decrease trespass events. Heatmaps also were generated for all trespass events in the camera's field of view (Figure 20) and from a transformed aerial view (Figure 21).

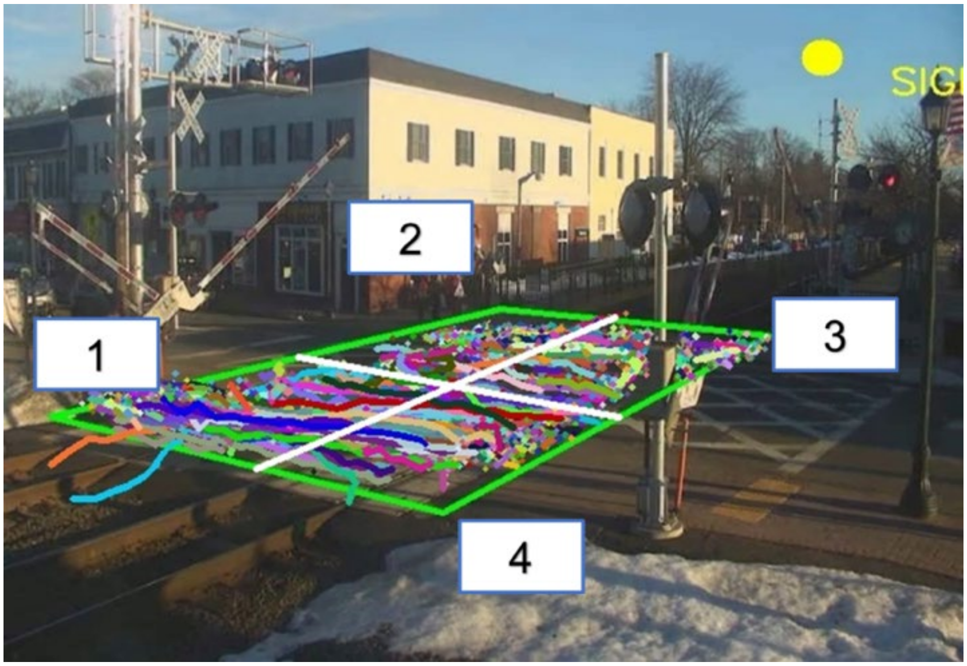


Figure 19. New Jersey Trespass Event Trajectories

The intensity of the heatmaps was generated using the first coordinates, or starting point, of each detected object. This was done to understand the origin of the trespass events. In terms of the normal-view trespass event heatmap, two hotspots are identified in Zones 1 and 3, which can provide more evidence to inform potential trespass event mitigation decisions.

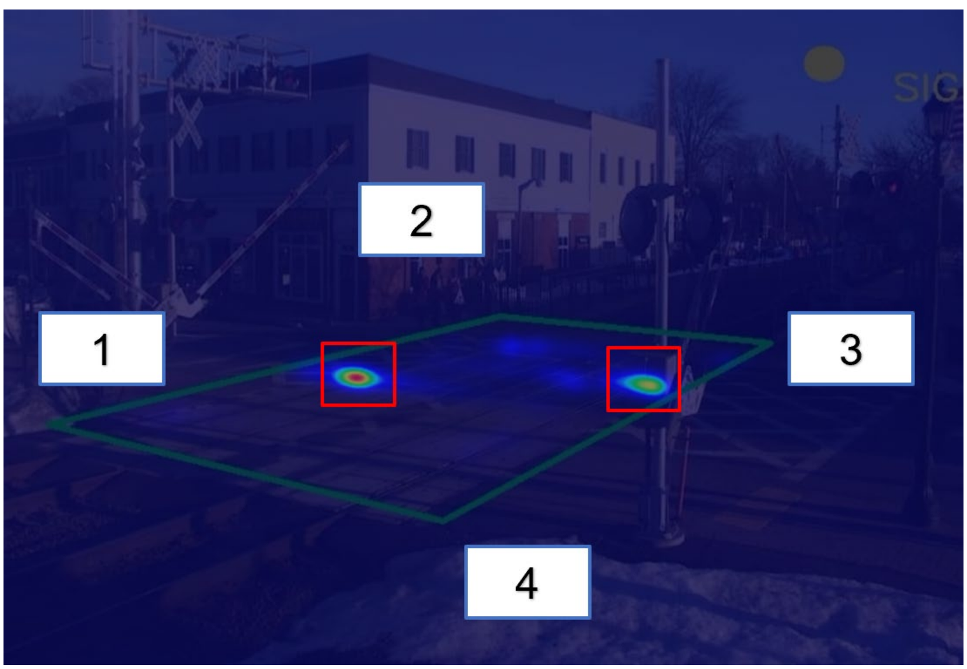
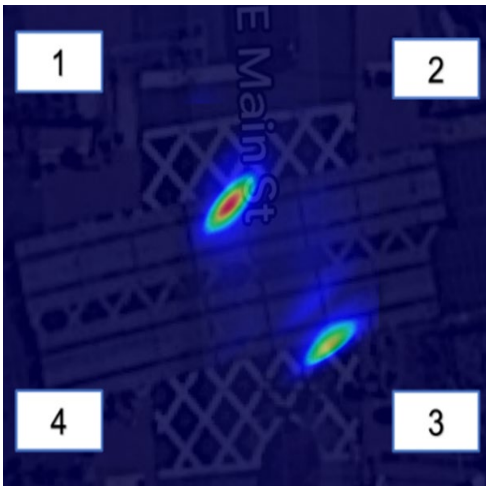


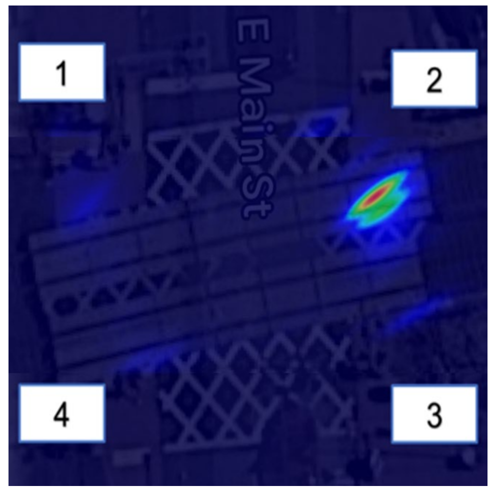
Figure 20. New Jersey Grade Crossing Normal-view Trespass Events Spatial Heatmap

Car and truck trespass events originated in Zone 1 and ended in Zone 4 more often than they originated in Zone 3 and ended in Zone 2. One hypothesis is that the traffic flow could be heavier on the Zone 1 to Zone 4 side, resulting in more frequent trespass events. Trajectory information was not recorded for traffic data, so researchers were unable to validate this hypothesis in this study. Another hypothesis is that signage is insufficient or unclear in Zone 1, increasing the potential for trespass events. More evidence is needed to validate both hypotheses.

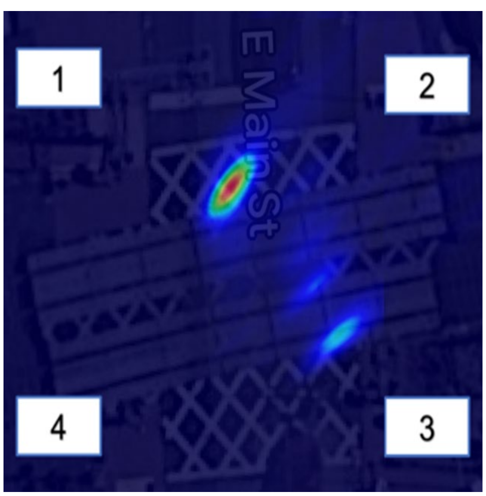
The pedestrian trespass event trajectory heatmap indicates that pedestrians and bicycles are more likely to violate Zone 2. Such behaviors by pedestrians and bicycles add more evidence to the assumption made in the "trespass event distribution by time and day" section that pedestrians need to cross the grade crossing upon arrival at the station (Zone 2) to reach the parking lots on the other side (Zones 3 and 4) during the evening commute. Since the number of bus trespass events is significantly lower than the other four types of trespass events, more data is needed to investigate bus trespass event behaviors.



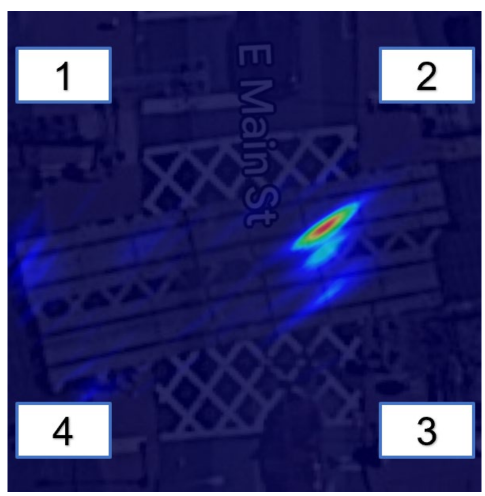
(a) Car Trespass Event Heatmap



(b) Pedestrian Trespass Event Heatmap



(c) Truck Trespass Event Heatmap



(d) Bicycle Trespass Event Heatmap

Figure 21. New Jersey Trespass Event Aerial-view Heatmap of (a) Cars, (b) Pedestrians, (c) Trucks, and (d) Bicycles

Table 7 shows the origin and destination analysis of four zones of trespass events for 10,334 events, or 52 percent of all trespass events. A limited selection of trajectories was chosen due to incomplete trajectory arrays for some of the trespass events. This may have been caused by occlusions or loss of tracking by the system. Occlusions would cause more errors in the Zone 2 to Zone 3 pair because the traffic lane is further from the camera and more likely to be obscured by traffic in the nearby lane. When combining all trespass events, there are three directions (Zone 1 to Zone 4, Zone 2 to Zone 3, and Zone 3 to Zone 2) worthy of particular attention. These three directions account for 85 percent of the total number of trespass events (8,792 out of 10,334 trespass events).

Table 7. New Jersey Trespass Events by Zone Origin and Destination

		Destination Zone			
		Zone 1	Zone 2	Zone 3	Zone 4
Origin Zone	Zone 1		184	178	**3,380**
	Zone 2	74		**1,456**	338
	Zone 3	39	**3,956**		194
	Zone 4	414	32	89	

5.1.4 Data Insights and Recommendations

5.1.4.1 Risk Based Patrols

Approximately 35 percent of trespass events occurred from 5 P.M. to 8 P.M. on weekdays, which corresponds with commuter schedules. Most trespass events occurred from 7 P.M. to 8 P.M. on Fridays. However, when normalized by traffic, all classes were less compliant during morning weekday rush hours. FRA (Horton & DaSilva, 2020) identifies law enforcement strategies for reducing trespass events, which include increasing enforcement patrols on targeted trespass event hotspots. Risk-based police patrols could be introduced to target temporal hotspots to reduce trespass events most efficiently at this crossing.

The team found that most trespass events occur in the summer. Enforcement blitzes could be scheduled during the summer to further decrease unsafe grade crossing behavior. Approximately 7,000 unsafe grade crossing events (35 percent) might be prevented by patrols targeted at the weekday hotspots during the summer season. If a targeted enforcement program is initiated, further studies should be conducted to understand the effectiveness of enforcing compliance during hours with peak trespass events, or during hours with the least compliance normalized by traffic volumes.

5.1.4.2 Targeted Education Blitzes

Targeted and timed safety education blitzes for the surrounding communities could reduce trespass events. The highest rate of trespass events by cars was in June and the highest rate of trespass events by pedestrians was in July. Therefore, more education about the legal and safety consequences of trespass events could be provided to the public during these months to reduce the likelihood of trespassing events. Four bus trespass events were detected at this grade crossing; even though this was the smallest of all detected classes, buses represent a high-risk scenario if an incident were to occur. Bus driver education should be reinforced to further reduce trespass events. Education materials like posters and warning signs could also be provided near the grade crossing to promote public education and reduce trespass events. Deployment of this strategy would mean that about 8,700 trespass events per year (43 percent) could be mitigated.

5.1.4.3 Additional Pedestrian Channelization

Researchers from the U.S. Department of Transportation (Chase et al., 2013) analyzed the impact of gate skirts on pedestrian behavior at highway-rail grade crossings and found that when the gate skirts are descending and horizontal, they reduce the number of trespass events. In that case study, vehicles, pedestrians, and bicycles accounted for 76, 23, and 1 percent of the total trespass events, respectively. At this crossing, a study by FRA and the Volpe Center showed a 19 percent reduction in trespass events after gate skirts were introduced (Bedini-Jacobini & DaSilva, 2020).

Pedestrians continue to violate the crossing by circumventing the gates, stepping around them and into the roadway. Figure 21 shows that most trespass events originate from Zone 2 of the crossing. Pedestrian channelization devices could be introduced near the pedestrian gates to further discourage circumvention of the safety measures, as described in Figure 22. The effectiveness of this countermeasure could be evaluated by further monitoring and analysis.

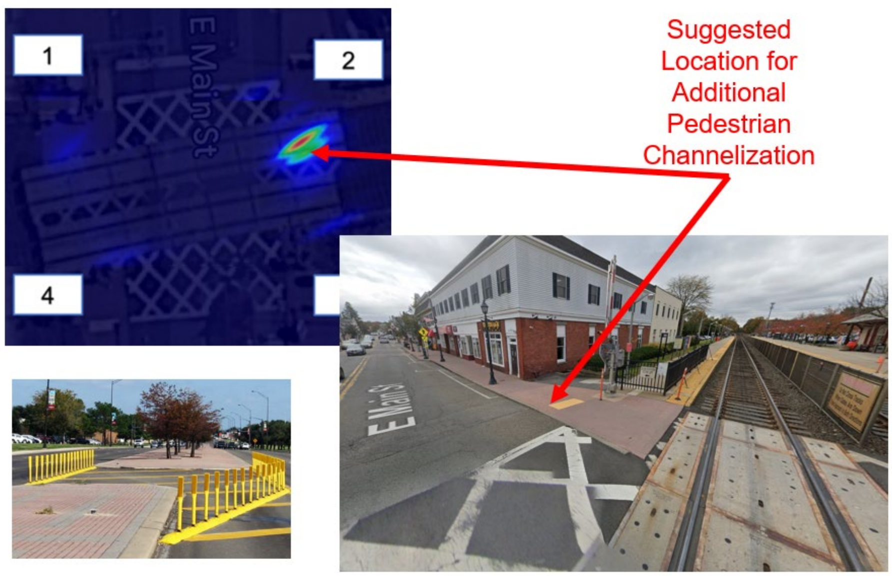
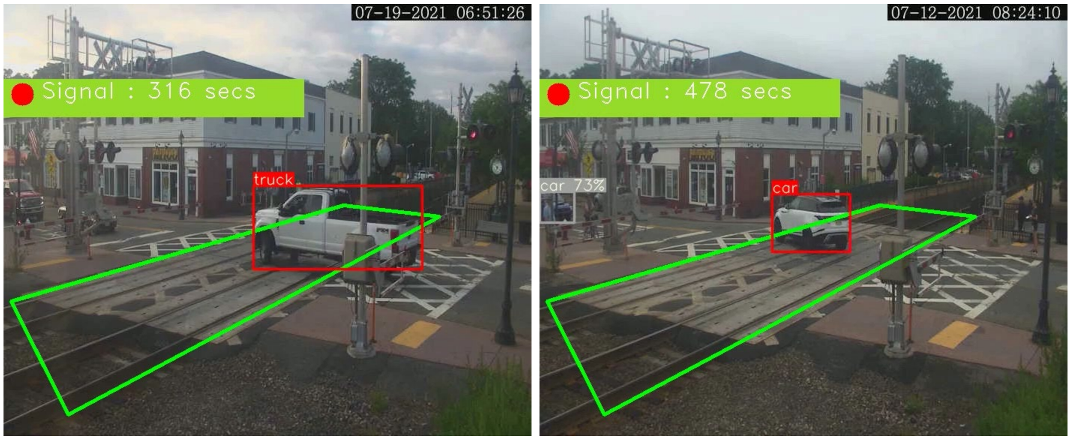


Figure 22. Suggested Location for Additional Pedestrian Channelization at the New Jersey Grade Crossing

5.1.4.4 Photo Enforcement

Vehicles were observed driving around the gates at the grade crossing during the study period. Figure 23 shows several examples of these types of events.

A potential solution to prevent these events is the implementation of red-light cameras and/or license plate readers to automatically issue fines and tickets to violators who run red lights or drive around the crossing gates. Photo enforcement systems at a grade crossing have been shown to reduce trespass event rates by 17 percent in past research (Ngamdung et al., 2019; Ngamdung & DaSilva, 2019). However, the use of this type of technology is subject to debate. According to a report by the National Conference of State Legislatures, 23 states have established red light camera pilots or programs, while 7 states have statutes prohibiting their use (National Conference of State Legislatures, 2022).



(a) **(b)**

Figure 23. New Jersey Grade Crossing Drive Around Gates Trespass Events

Instead of issuing fines and tickets, a study in Florida tested the use of red light cameras to issue educational material to those who violated a crossing (Ngamdung & DaSilva, 2019). The results of this study showed that the trespass event rate was reduced "by 15.4 percent from the pre- to the post-test period" (Ngamdung & DaSilva, 2019). The limitation of this system is that it would only apply to vehicle trespass events and may require human intervention to officially issue educational material or fines.

5.2 North Carolina Right of Way Case Study

5.2.1 Location Description

Two cameras were present at this section of ROW in North Carolina, one facing north and the other south. The following analysis covers the north facing camera. Analysis of trespass events from the south facing stream can be found in Appendix B. A satellite view of the ROW can be seen in Figure 24. It is located near a downtown district with shopping centers, schools, and restaurants. According to the latest U.S. Census estimates, the current population of the town where this crossing is located is 27,000.

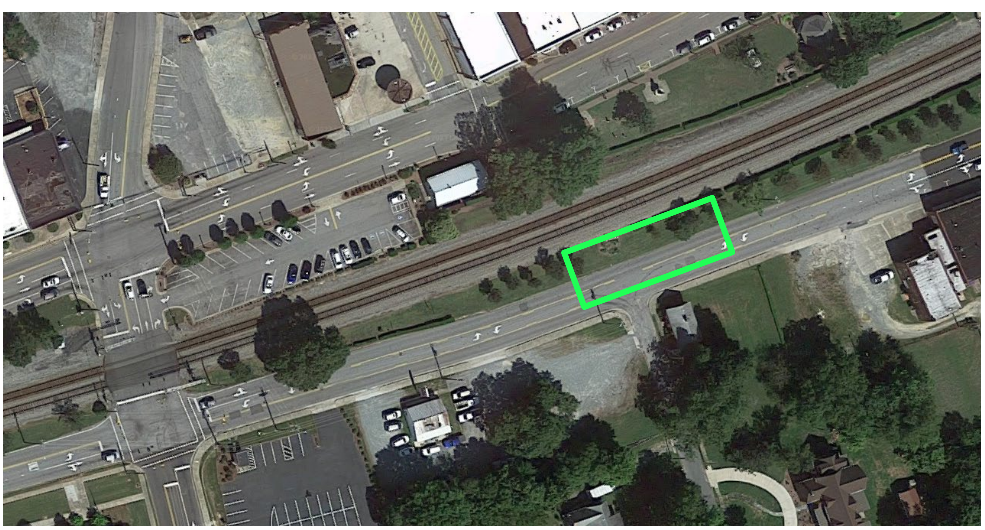


Figure 24. North Carolina ROW North Camera Satellite View

For this research, the video stream was obtained from Virtualrailfan. In this case study, 302 days (7,248 hours) of live video data was analyzed from January 1, 2021, to January 31, 2022. This video stream was continuously monitored by the AI for 24 hours each day of the study period. However, the video stream was sporadically unavailable due to periodic maintenance and intermittent connection issues at the site. The video format is MP4 with a resolution of 1920 x 1080 pixels and 30 frames per second.

5.2.2 Data Collection and Validation

The system correctly identified 476 trespass events during the study period. A trespass event represents an occurrence that may consist of multiple trespassers within a single record or video clip. In the event dataset, information such as trespasser type (e.g., car, pedestrian, truck, bus, bicycle), start and end date and time, event duration, trajectory, video link, weather, and temperature were stored. The weather information was obtained from OpenWeather API. Even though the AI could identify multiple classes of trespassers, only pedestrian trespassers were detected during the analysis period.

All records were manually reviewed and validated by the research team to ensure all trespass events were correctly identified. The system identified 492 total events, of which 476 (~97 percent) were true and 16 (~3 percent) were false positives. False positive rates were used to evaluate the system's performance. There were two main causes of false positives discovered in the trespass event dataset: legal occupiers (11 events) and misclassifications (5 events). Examples of the types of false positives can be seen in Figure 25.

(a) Misclassification **(b) Legal Occupier**

Figure 25. North Carolina ROW North Camera Example False Positives caused by (a) Misclassifications and (b) Legal Occupiers

Misclassifications were ameliorated by retraining the AI using annotated images from the dataset to increase detection confidence scores. A special legal occupier class is being developed to prevent the AI from flagging railroad workers and hi-rail vehicles as trespassers.

To detect missed detections, the team performed a series of 24-hour manual reviews of the system after deployment. During this analysis, the team members manually reviewed the raw video footage and identified all trespass and train events. The AI system then analyzed the same footage and reported the results. The two datasets were compared to determine the system's relative accuracy.

False negative rates were used to evaluate the dataset. False negative rates can be calculated by dividing the number of missed detections by the total number of actual trespass events. This analysis was performed three times during the study period: on February 10, 2021, June 14, 2021, and August 12, 2021. In each of these instances, no trespass events were missed by the system.

5.2.3 Case Study Results

The team analyzed 476 trespass events and visualized them from several perspectives, yielding weekly and hourly temporal heatmaps, monthly trespass event trends, and a trespass event spatial heatmap analysis. There were approximately 1.6 pedestrian trespass events per day during the study period.

5.2.3.1 Trespass Event Temporal Heatmap

Heatmaps of all pedestrian trespass events across one-hour intervals for each day of the week are shown in Figure 26. More trespass events occurred during daylight hours from 7 AM to 6 PM on all days of the week. Approximately 13.7 percent of all trespass events occurred between 3 P.M. and 4 P.M., which is the one-hour window with the highest percentage of trespass events. During the study period, over 48 percent of all trespass events occurred on the weekend. There were fewer trespass events at this location, therefore the temporal trends may be skewed and require longer monitoring to ascertain trespassing event patterns.

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	1	0	0	0	0	0	0	2	1	3	6	5	2	9	5	6	2	9	6	2	3	2	2	0	66
Tuesday	2	0	0	0	0	0	0	2	3	2	1	1	5	0	14	7	1	7	4	3	0	0	0	1	53
Wednesday	1	1	0	0	0	0	1	0	0	1	2	2	5	5	3	3	8	1	3	3	0	0	0	0	39
Thursday	3	0	0	0	0	0	2	2	2	2	10	5	5	4	3	1	2	4	0	0	0	0	0	0	45
Friday	5	0	0	0	0	0	1	0	2	2	2	3	7	2	0	6	3	1	3	0	2	1	0	0	40
Saturday	3	0	0	0	0	0	0	3	1	2	4	10	16	10	10	19	24	21	2	4	0	0	0	0	129
Sunday	1	0	0	0	0	0	0	0	1	2	4	3	3	32	24	27	0	1	2	0	2	0	2	0	104
Grand Total	**16**	**1**	**0**	**0**	**0**	**0**	**4**	**9**	**10**	**14**	**29**	**29**	**43**	**62**	**59**	**69**	**40**	**44**	**20**	**12**	**7**	**3**	**4**	**1**	**476**

Figure 26. North Carolina ROW North Camera Trespass Event Heatmaps by Time and Day (January 1, 2021, to December 31, 2021)

These temporal hotspots differ from the grade crossing temporal heatmaps, indicating different trespass event behaviors. This location's trespass events were more likely to occur on weekends and were driven by specific local events covered in Section 5.2.3.2. However, this temporal heatmap can be used to implement risk-based patrols to ameliorate trespass events and measure the effects of any implemented mitigation strategy.

5.2.3.2 Trespass Events by Month of Year

The number of trespass events is summarized by month in Figure 27. No data was collected during February 2021 when the stream was unavailable due to system maintenance.

There were disproportionately more trespass events in September 2021 and November 2021. During these months, many trespass events occurred on single days. Forty-six trespass events occurred on September 25, 2021, and 80 trespass events occurred on November 28, 2021. Each of these spikes in trespass events coincided with public events. On September 25, the township hosted an "Everybody's Day Festival" and on November 28, the township hosted a Christmas Parade. Figure 28 shows many trespassers present during the Christmas Parade event.

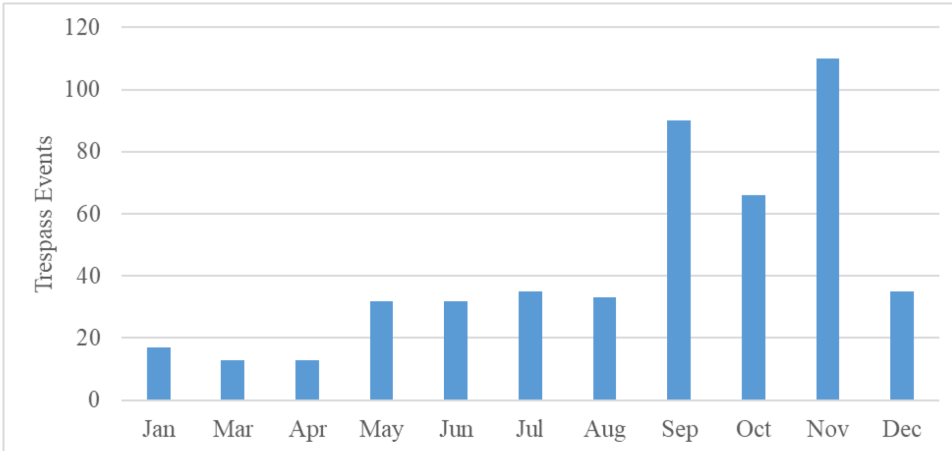


Figure 27. North Carolina ROW North Camera Trespass Event Heatmaps by Month (January 1, 2021, to December 31, 2021)

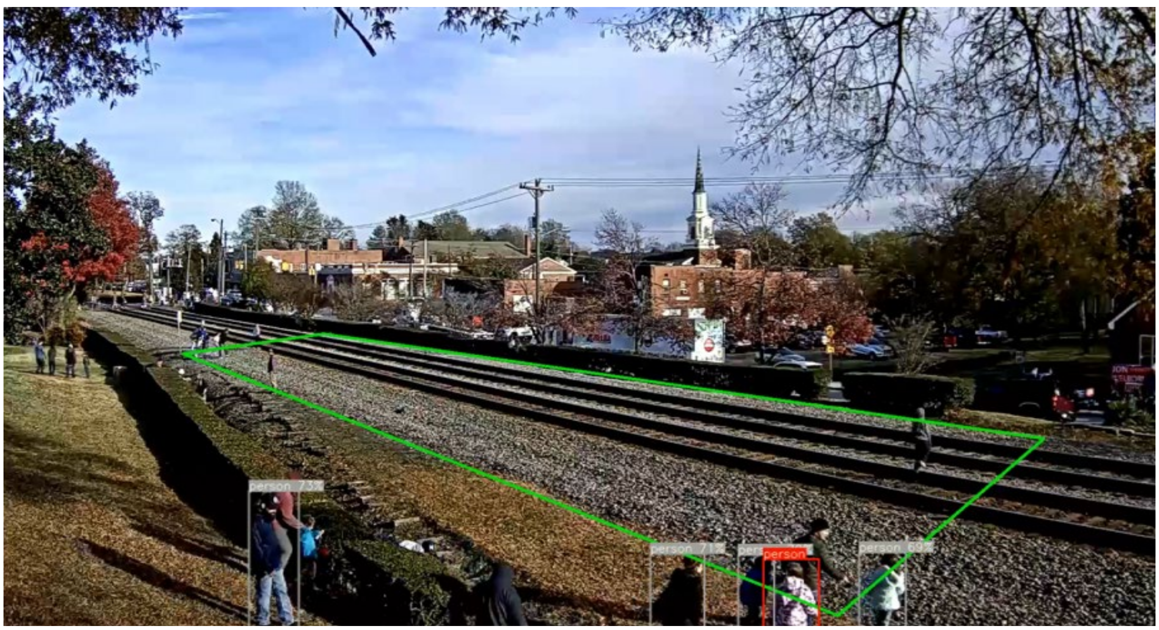


Figure 28. North Carolina ROW North Camera Christmas Parade Event Trespassers on November 28, 2021

Local enforcement blitzes could precede and coincide with planned events to prevent trespassing and reduce the risk of a pedestrian strike. This system could be used to identify and alert local authorities when trespass events exceed a learned threshold, informing them of the need for a targeted response.

5.2.3.3 Trespass Event Spatial Heatmap Analysis

A spatial heatmap was generated for all trespass events in the camera's field of view and is shown in Figure 29, and an aerial view is shown in Figure 30. The intensity of the heatmap is generated using the first coordinates, or starting point, of each detected object. This helps in understanding the origin of trespass events and can thus inform trespass event mitigation strategies.

Figure 29. North Carolina ROW North Camera Trespass Event Spatial Heatmap for All Classes with Origin and Destination Zones (January 1, 2021, to January 31, 2022)

The trespass event spatial heatmap indicates that pedestrians are more likely to originate from Zone 1 than Zone 2. Additionally, trespass event origin points are more spread out in Zone 1 than in Zone 2, indicating that trespass events converge at a single point in Zone 2. The convergence of these paths is further reinforced by Figure 30.

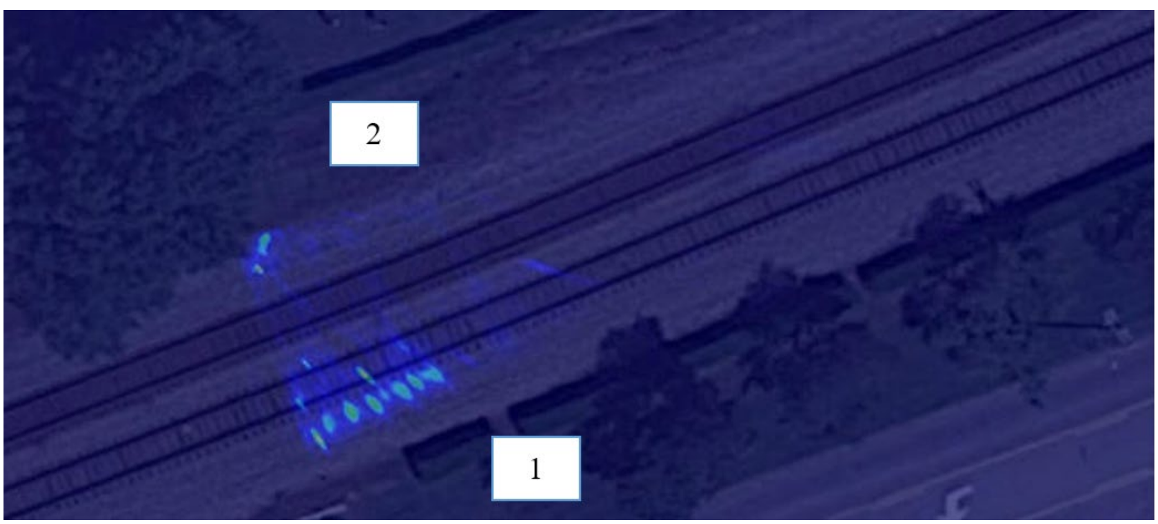


Figure 30. Heatmap of Aerial-view Total Trespass Events

This spatial heatmap can be used to design more effective engineering solutions. Knowing the exact paths of trespassers could justify the installation of fencing or deterrent vegetation (hedges, bushes, etc.) and landscaping. This system could be used to measure the effectiveness of the installed solution and to calculate the cost-benefit ratio for the investment.

5.2.4 Data Insights and Recommendations

5.2.4.1 Targeted Education

The automatic aggregation of trespass event video can offer insight into trespass event behaviors, which can then lead to specific targeted solutions. Several protracted trespass events were observed in May 2021. During one of these two events, two people were observed taking graduation photos on the tracks, as seen in Figure 31. In this event, the two people were on the tracks for two minutes and five seconds.

Figure 31. Trespassers Taking Graduation Photos on the ROW

This presents an opportunity for a targeted educational solution. Research by the Volpe Center has shown that public education and enforcement programs like the Program for the Education and Enrichment of Relational Skills (PEERS) have been "successful in curbing overall violations and the most risky pedestrian violations" (Horton, 2011). Local authorities and Operation Lifesaver could target nearby schools for educational blitzes in the months preceding graduation to discourage this behavior. Enforcement patrols could pass by this crossing to remove trespassers from railroad property to reduce the risk of a trespasser strike. Additionally, this system could continue to monitor the ROW, measure the effectiveness of such countermeasures, and alert law enforcement of violators if the trespass event duration exceeds an established threshold.

5.2.4.2 Enforcement Blitzes

Large spikes in the number of trespass events surrounding local events present an opportunity to reduce trespassing. Railroad and local police could conduct enforcement blitzes in the weeks preceding and on the days of large events. Figure 32 shows a potential enforcement blitz schedule covering potential periods before local events. A study by FRA, the Volpe Center, and four communities in Lake Worth, FL, Worcester, MA, North Tonawanda, NY, and Brighton, NY, investigated the effect of enforcement efforts and found that there were dramatic decreases in violations when patrols were conducted (Horton & DaSilva, 2020).

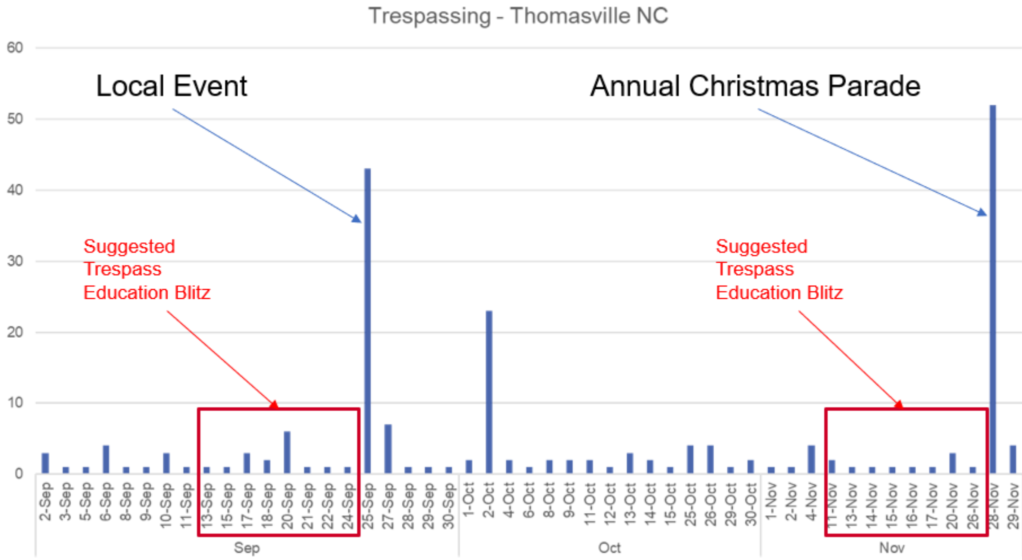


Figure 32. North Carolina ROW Suggested Enforcement Blitz Time Periods

5.2.4.3 Fencing Installation and Landscaping

Landscaping and fencing have proven to be effective solutions for railroad trespassing. A study by Silla (2013) investigated the effects of installing 200 yards of fencing for 30,000 € (approximately $40,000 in 2013), 200 yards of 4.5-foot-tall landscaping for 30,000 €, and no-trespassing signs for 5,000 € (approximately $6,675 in 2013). Trespassing was manually observed for week-long periods both before and one year after the installation. These solutions were shown to significantly reduce trespassing, as seen in Figure 33.

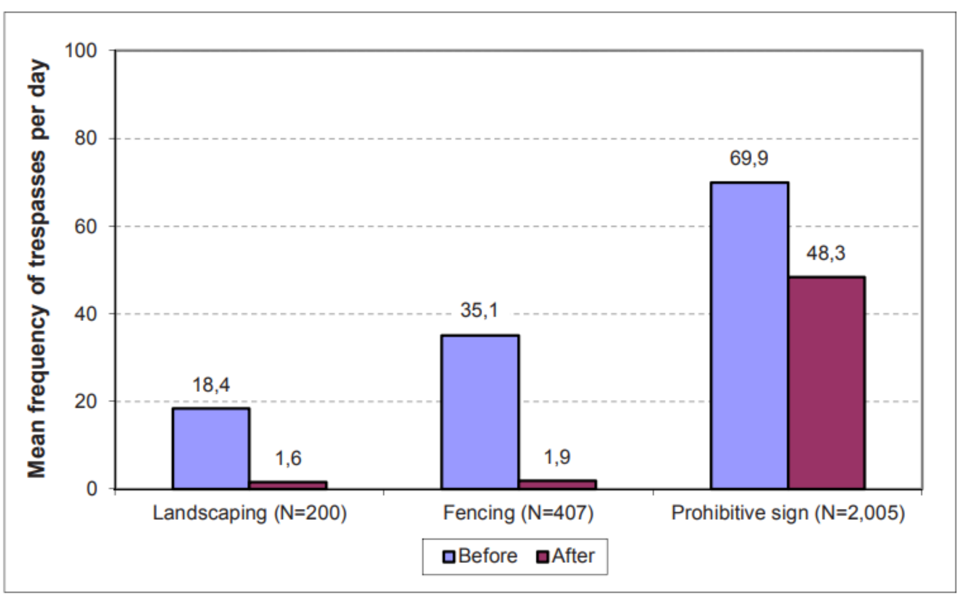


Figure 33. Effects of Landscaping in a Finnish Case Study (Silla & Luoma, 2011)

The implementation of similar solutions could be justified by the volume of trespassers identified in this study. Figure 34 shows the trespasser origin hotspots along the observed red ROW. Existing vegetation is in disrepair with gaps trespassers might use to cross railroad property. If a single side of this location were enhanced with taller and fuller vegetation or fencing, all trespass events might be eliminated. The cost-benefit of this installation and continued maintenance could be justified by continued monitoring and measuring of the reduction in trespassers.

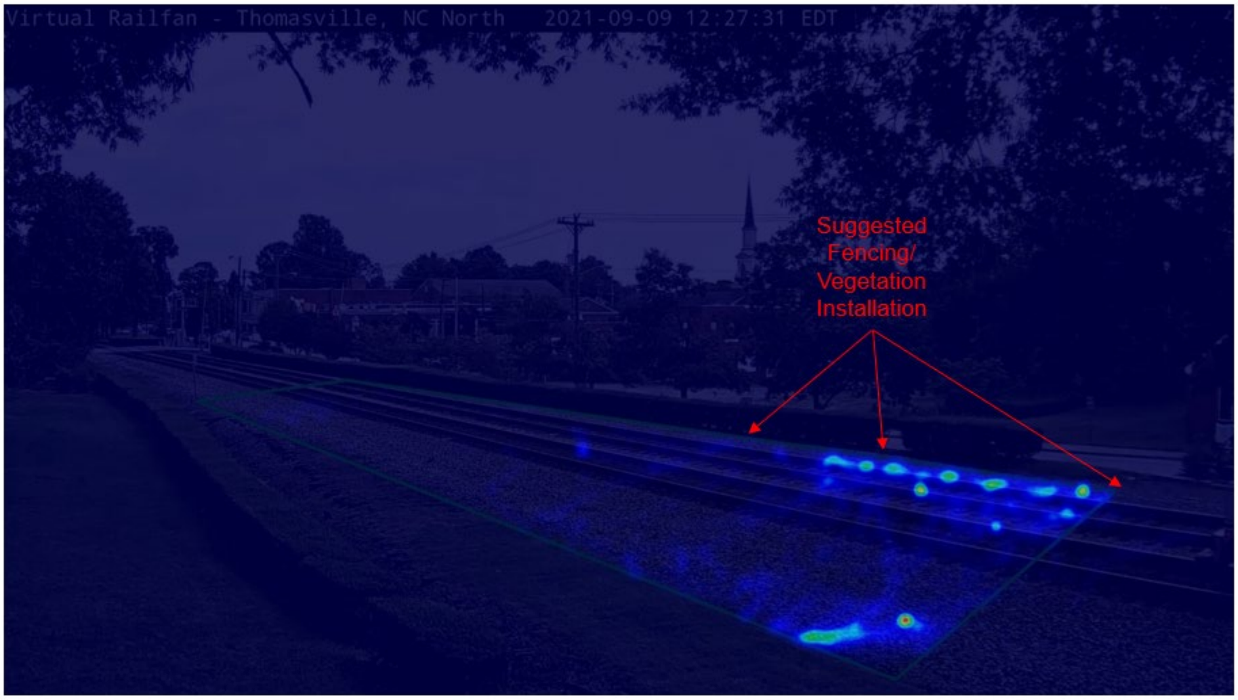


Figure 34. North Carolina ROW Suggested Fencing or Landscaping

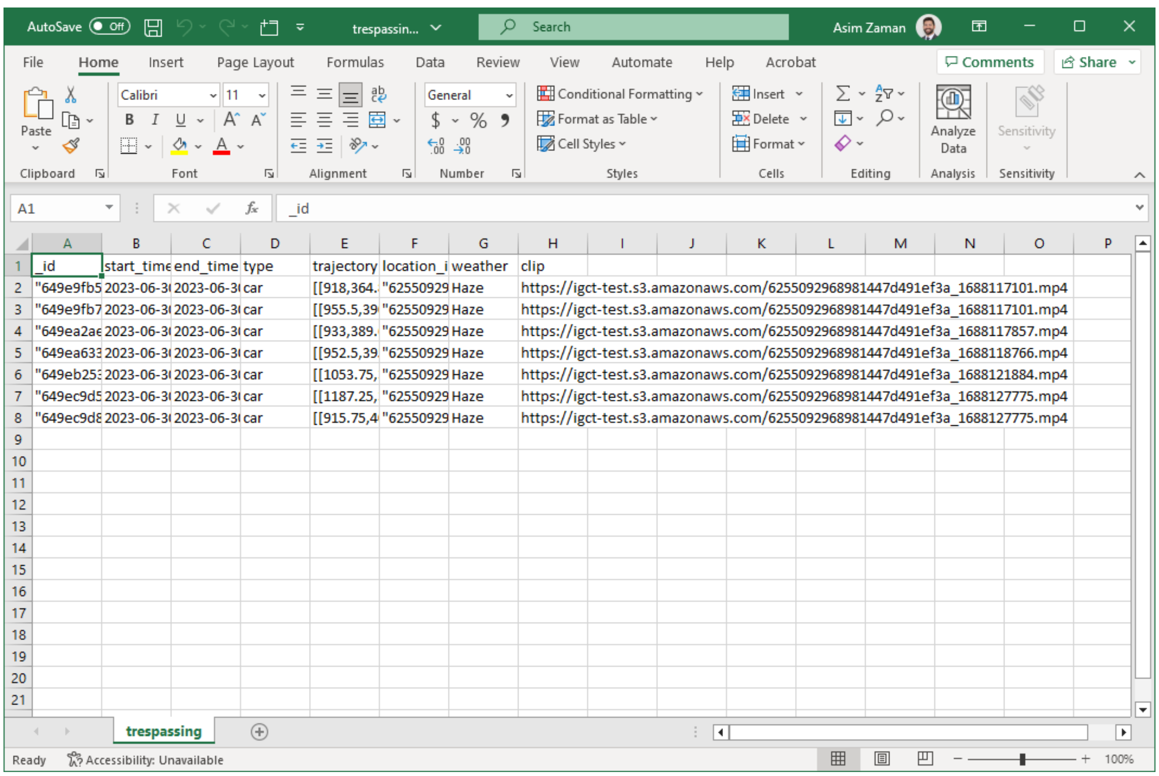
6. Data Analytics Tool

To encourage technology transfer and increase the impact of this research, a dashboard was created and made available to the public to view and analyze the aggregated database. The following section describes the database structure and the publicly available dashboard.

6.1 Database Structure

Metadata records are stored in a MongoDB structure and can be queried by a prototype dashboard. Four datasets can be generated in comma separated values (csv) format: traffic, trespass event, signal, and train. When a user queries the database, the requested csv files are downloaded to the user's local computer in a zip file. Video records are stored in an Amazon S3 storage bucket and can be accessed by hyperlinks provided in the queried csv files. The following screenshots show images of generated csv files.

6.1.1 trespassing.csv



_id	start_time	end_time	type	trajectory	location_i	weather	clip
"649e9fb5	2023-06-3	2023-06-3	car	[[918,364.	"62550929	Haze	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688117101.mp4
"649e9fb7	2023-06-3	2023-06-3	car	[[955.5,39	"62550929	Haze	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688117101.mp4
"649ea2ae	2023-06-3	2023-06-3	car	[[933,389.	"62550929	Haze	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688117857.mp4
"649ea633	2023-06-3	2023-06-3	car	[[952.5,39	"62550929	Haze	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688118766.mp4
"649eb253	2023-06-3	2023-06-3	car	[[1053.75,	"62550929	Haze	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688121884.mp4
"649ec9d5	2023-06-3	2023-06-3	car	[[1187.25,	"62550929	Haze	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688127775.mp4
"649ec9d8	2023-06-3	2023-06-3	car	[[915.75,4	"62550929	Haze	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688127775.mp4

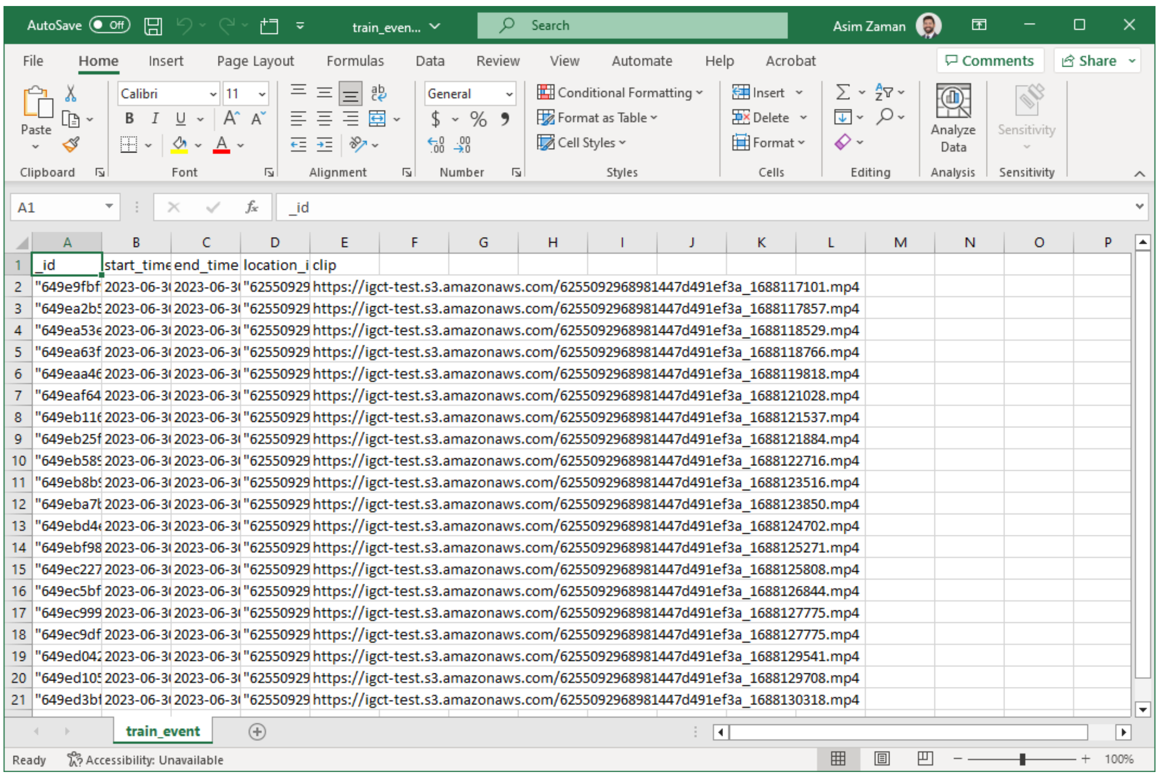
Figure 35. Example trespassing.csv

trespassing.csv files contain the following information:

_id	a unique ID assigned to the individual trespassing record.
start time	UTC time when the AI first recognized the trespasser.
end time	UTC time when the AI last recognized the trespasser.
type	AI classification of the trespasser
	{car, truck, bus, bicycle, person, motorcycle}

Trajectory	An array of coordinates defined by the following structure [x,y,w,h,f] x: horizontal pixel coordinate of the center of the trespasser y: vertical pixel coordinate of the center of the trespasser w: width of the trespasser's bounding box h: height of the trespasser's bounding box f: frame in the signal video clip where the trespasser is recognized.
Location	a unique ID assigned to the location in the database.
Weather	local weather obtained from an OpenWeather API
Clip	hyperlink to the trespass event clip

6.1.2 *train_event.csv*



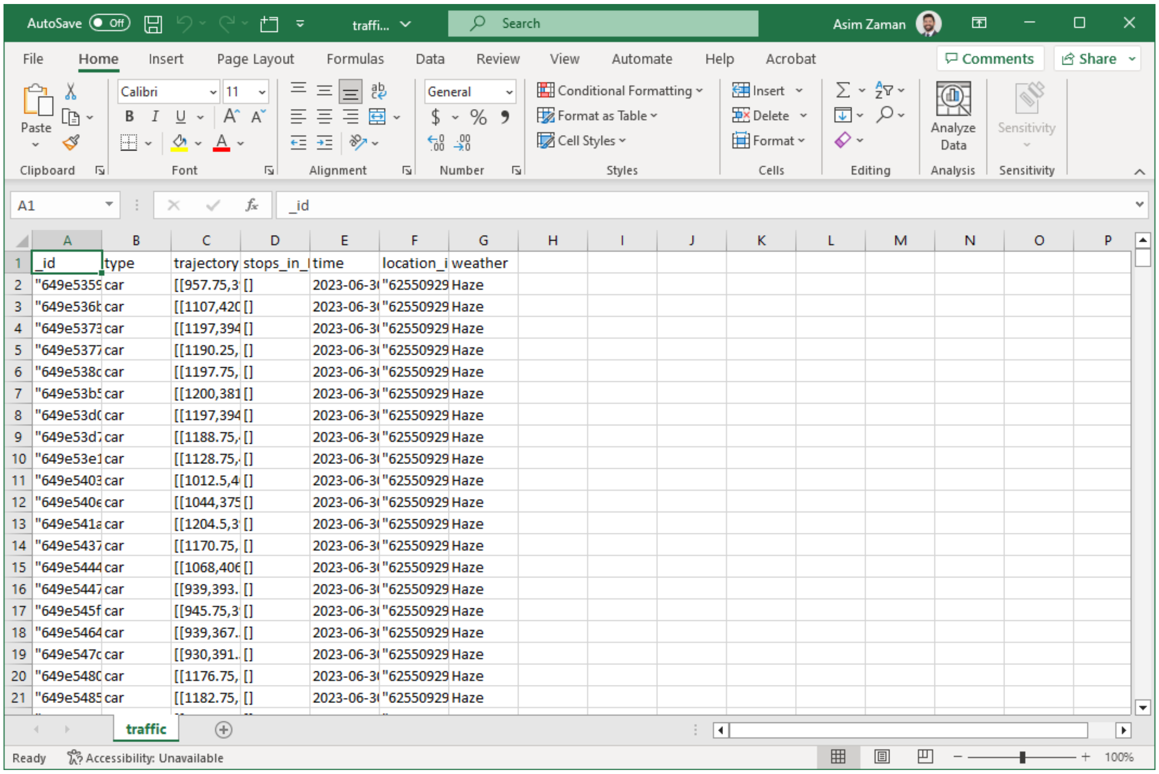
	A	B	C	D	E
1	_id	start_time	end_time	location_i	clip
2	"649e9fbf	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688117101.mp4
3	"649ea2b	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688117857.mp4
4	"649ea53	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688118529.mp4
5	"649ea63f	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688118766.mp4
6	"649eaa4	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688119818.mp4
7	"649eaf64	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688121028.mp4
8	"649eb11	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688121537.mp4
9	"649eb25f	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688121884.mp4
10	"649eb58	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688122716.mp4
11	"649eb8b	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688123516.mp4
12	"649eba7	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688123850.mp4
13	"649ebd4	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688124702.mp4
14	"649ebf98	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688125271.mp4
15	"649ec227	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688125808.mp4
16	"649ec5bf	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688126844.mp4
17	"649ec999	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688127775.mp4
18	"649ec9df	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688127775.mp4
19	"649ed04	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688129541.mp4
20	"649ed10	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688129708.mp4
21	"649ed3b	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/6255092968981447d491ef3a_1688130318.mp4

Figure 36. Example train_event.csv

train_event.csv contains the following information:

_id	a unique ID assigned to the individual train event record.
start time	UTC time when the train was first recognized by the AI system.
end time	UTC time when the train was last recognized by the AI system.
Location	a unique ID assigned to the location in the database.
Clip	hyperlink to the train event clip

6.1.3 *traffic.csv*



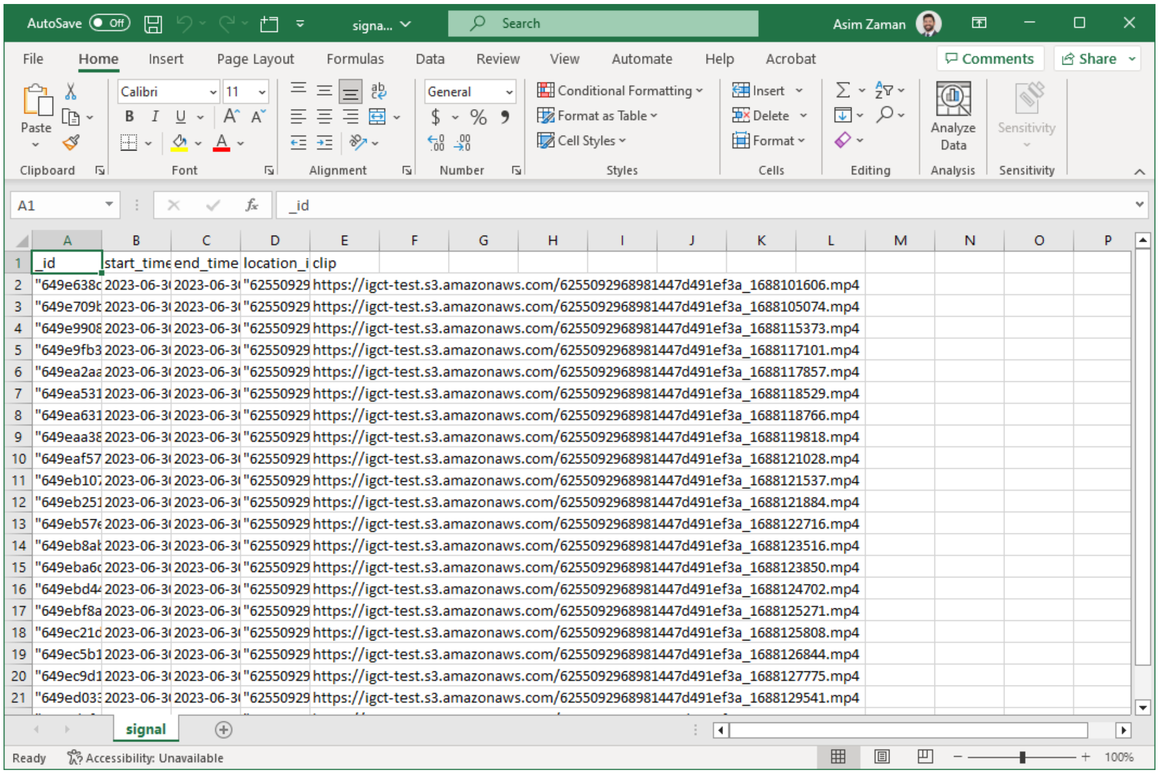
	_id	type	trajectory	stops_in_	time	location_i	weather
2	"649e5359	car	[[957.75,3	[]	2023-06-3	"62550929	Haze
3	"649e536b	car	[[1107,420	[]	2023-06-3	"62550929	Haze
4	"649e5373	car	[[1197,394	[]	2023-06-3	"62550929	Haze
5	"649e5377	car	[[1190.25,	[]	2023-06-3	"62550929	Haze
6	"649e538c	car	[[1197.75,	[]	2023-06-3	"62550929	Haze
7	"649e53b5	car	[[1200,381	[]	2023-06-3	"62550929	Haze
8	"649e53d0	car	[[1197,394	[]	2023-06-3	"62550929	Haze
9	"649e53d7	car	[[1188.75,	[]	2023-06-3	"62550929	Haze
10	"649e53e1	car	[[1128.75,	[]	2023-06-3	"62550929	Haze
11	"649e5403	car	[[1012.5,4	[]	2023-06-3	"62550929	Haze
12	"649e540e	car	[[1044,375	[]	2023-06-3	"62550929	Haze
13	"649e541a	car	[[1204.5,3	[]	2023-06-3	"62550929	Haze
14	"649e5437	car	[[1170.75,	[]	2023-06-3	"62550929	Haze
15	"649e5444	car	[[1068,406	[]	2023-06-3	"62550929	Haze
16	"649e5447	car	[[939,393.	[]	2023-06-3	"62550929	Haze
17	"649e545f	car	[[945.75,3	[]	2023-06-3	"62550929	Haze
18	"649e5464	car	[[939,367.	[]	2023-06-3	"62550929	Haze
19	"649e547c	car	[[930,391.	[]	2023-06-3	"62550929	Haze
20	"649e5480	car	[[1176.75,	[]	2023-06-3	"62550929	Haze
21	"649e5485	car	[[1182.75,	[]	2023-06-3	"62550929	Haze

Figure 37. Example traffic.csv

traffic.csv files contain the following information:

_id	a unique ID assigned to the individual traffic record.
start time	UTC time when the AI first recognized the traffic.
end time	UTC time when the AI last recognized the traffic.
type	AI classification of the traffic {car, truck, bus, bicycle, person, motorcycle}
trajectory	an array of coordinates defined by the following structure [x,y,w,h,0] x: horizontal pixel coordinate of the center of the trespasser y: vertical pixel coordinate of the center of the trespasser w: width of the trespasser's bounding box h: height of the trespasser's bounding box
Location	a unique ID assigned to the location in the database.
Weather	local weather obtained from an OpenWeather API

6.1.4 *signal.csv*



	A	B	C	D	E
1	_id	start_time	end_time	location_i	clip
2	"649e638c	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688101606.mp4
3	"649e709	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688105074.mp4
4	"649e9908	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688115373.mp4
5	"649e9fb3	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688117101.mp4
6	"649ea2a	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688117857.mp4
7	"649ea531	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688118529.mp4
8	"649ea631	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688118766.mp4
9	"649eaa38	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688119818.mp4
10	"649eaf57	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688121028.mp4
11	"649eb107	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688121537.mp4
12	"649eb251	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688121884.mp4
13	"649eb57	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688122716.mp4
14	"649eb8a	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688123516.mp4
15	"649eba6	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688123850.mp4
16	"649ebd4	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688124702.mp4
17	"649ebf8a	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688125271.mp4
18	"649ec21d	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688125808.mp4
19	"649ec5b1	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688126844.mp4
20	"649ec9d1	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688127775.mp4
21	"649ed03	2023-06-3	2023-06-3	"62550929	https://igct-test.s3.amazonaws.com/625509296981447d491ef3a_1688129541.mp4

Figure 38. Example signal.csv

signal.csv files contain the following information:

_id	a unique ID assigned to the individual signal record.
start time	UTC time when the AI first recognized the signal.
end time	UTC time when the AI last recognized the signal.
Location	a unique ID assigned to the location in the database.

6.2 Visualization Tool and Publicly Available Dataset

The research team plans to make selected trespass event metadata and video clips available via a Visualization Tool, while pages for each location covered in this study are available through the dashboard. While the scope is limited to the locations and periods covered in the study, the system should provide stakeholders with a concept of the type of data and potential analyses that could be conducted. The dashboard will soon be available through the Rutgers Rail and Transit Team's Trespass Database (http://rail.rutgers.edu/trespassdatabase). An example of the analysis dashboard is shown in Figure 39.

Trespass Event Temporal Heatmap

Day of Week	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Total
1 Sunday	61	42	18	3		13	43	95	114	59	63	46	69	67	105	30	145	106	154	223	140	38	101	30	1765
2 Monday	33	12	7		9	68	177	192	174	98	56	81	96	97	87	168	175	306	272	338	333	79	71	42	2971
3 Tuesday	34	17	4	3	11	105	214	222	196	111	44	83	75	136	104	205	200	362	316	426	374	112	81	44	3479
4 Wednesday	30	26	11	1	11	90	220	231	276	137	62	69	99	123	99	203	237	372	347	422	370	98	94	41	3669
5 Thursday	30	23	12	5	11	96	200	188	267	145	78	116	114	115	129	202	253	453	368	423	386	135	77	58	3884
6 Friday	30	28	19	1	5	97	183	177	209	128	61	82	84	104	99	200	217	391	363	446	353	120	81	50	3528
7 Saturday	48	53	12	1	2	21	59	125	123	53	90	25	79	97	113	30	166	131	158	169	112	40	138	60	1905
Total	**266**	**201**	**83**	**14**	**49**	**490**	**1096**	**1230**	**1359**	**731**	**454**	**502**	**616**	**739**	**736**	**1038**	**1393**	**2121**	**1978**	**2447**	**2068**	**622**	**643**	**325**	**21201**

Signal Activation Temporal Heatmap

Day of Week	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Total
1 Sunday	129	80	63	9	3	27	53	74	92	56	64	27	75	60	94	35	141	84	106	114	108	86	164	71	1815
2 Monday	106	71	47	30	31	105	120	109	133	94	64	86	102	100	107	161	155	225	199	224	266	140	130	74	2879
3 Tuesday	93	104	76	26	61	126	147	137	174	120	80	105	122	142	116	184	178	282	236	259	287	162	106	85	3408
4 Wednesday	87	137	71	41	42	140	157	161	189	124	103	90	117	130	119	207	196	247	204	256	278	139	123	68	3426
5 Thursday	89	101	62	21	48	121	155	127	187	151	103	104	115	115	112	170	185	286	213	239	275	146	115	86	3326
6 Friday	89	124	81	12	39	134	143	121	142	121	73	105	113	114	104	183	177	245	213	247	276	169	105	69	3199
7 Saturday	98	136	64	8	6	46	72	88	84	54	78	39	84	72	127	34	121	90	112	124	99	74	190	71	1971
Total	**691**	**753**	**464**	**147**	**230**	**699**	**847**	**817**	**1001**	**720**	**565**	**556**	**728**	**733**	**779**	**974**	**1153**	**1459**	**1283**	**1463**	**1589**	**916**	**933**	**524**	**20024**

Traffic Temporal Heatmap

Day of Week	01	02	03	04	05	06	07	08	09	10	11	12
1 Sunday	4342	2422	944	848	2076	5806	12850	20415	37122	51003	63432	65707
2 Monday	839	506	541	1146	4004	12432	33110	36715	32383	37529	45944	51649
3 Tuesday	840	529	652	1424	4838	14492	37358	40680	35958	42330	56056	64994
4 Wednesday	873	496	636	1305	5287	16062	41365	44948	40169	42793	55444	65763
5 Thursday	1262	673	607	1255	4269	12713	33571	38508	36789	41271	53749	60296
6 Friday	2909	1814	763	1302	4226	12352	34198	35912	35107	39998	49026	57171
7 Saturday	4658	2504	1021	1089	3295	9276	20937	30848	43639	54993	64899	67093
Total	**15723**	**8944**	**5164**	**8369**	**27995**	**83133**	**213389**	**248026**	**261167**	**309917**	**388550**	**432673**

Day of Week	13	14	15	16	17	18	19	20	21	22	23	Total
1 Sunday	60681	51852	46616	42394	38803	34118	27895	20140	13573	8067	4072	621819
2 Monday	53742	59848	59818	58123	56249	49196	37948	26398	18107	9390	4600	692138
3 Tuesday	66185	66386	68199	67281	66397	59306	43179	32232	21254	10875	5271	808721
4 Wednesday	68936	70171	69396	67989	67399	60638	45818	31550	22011	11478	5844	838464
5 Thursday	62647	67301	67974	66168	64846	57559	42761	31212	22067	13209	7390	790687
6 Friday	61040	64140	68938	67420	64326	59365	47645	34308	25986	19331	12525	803632
7 Saturday	64602	62206	58876	55052	51262	46476	38732	29854	21771	16848	11949	768777
Total	**437833**	**441904**	**439817**	**424427**	**409282**	**366658**	**283978**	**205694**	**144769**	**89198**	**51651**	**5324238**

Figure 39. Example Microsoft Power BI Dashboard for New Jersey Grade Crossing

This dashboard provides three temporal heatmaps (i.e., Trespass Event Temporal Heatmap, Signal Event Temporal Heatmap, and Traffic Temporal Heatmap) and two filters (i.e., a date filter and a class filter). The date filter allows the user to select a date range and view the associated events that occurred within that range. The class filter allows the user to select one or multiple object classes and generate trespass event and traffic heatmaps.

7. Conclusion

FRA contracted with a research team to develop a trespass event database using Artificial Intelligence technology developed by Rutgers University. This AI system automatically generated key metadata and video clips by analyzing video live streams and recorded video data from grade crossings and ROW. The system collected traffic data by class, train event data, signal activation data, and trespass event data. Data were automatically collected for each trespass event, including date, time, type (e.g., person, car, truck, bus, etc.), weather, trespasser's path, and a video clip. All results in the database were manually reviewed by the team to ensure accuracy. False positive and false negative results were used to further improve the AI system throughout the study's duration.

This AI system processed over 50,000 hours of live and recorded video data at nine grade crossings and two ROW locations in six states. Four locations, two crossings, and two ROW were analyzed for one year, while the other locations were each studied for approximately one week. Over 29,000 trespass events were captured during the study across all locations.

Two year-long, detailed case studies were presented in this report. In the first case study, 21,202 trespass events from one grade crossing in New Jersey were analyzed, yielding temporal trespass event heatmaps, trespass event summaries by season and month, a near-miss analysis, and a spatial analysis. In the second case study, 476 trespass events from one ROW location in North Carolina were analyzed, yielding temporal trespass event heatmaps, monthly trespass event trends, and a spatial trespass event origin analysis. AI data-informed solutions were presented for each location, using the trespass event database and the latest literature on solution effectiveness for justification.

Finally, a dashboard was created and made available to the public to view and analyze the aggregated database. Additional analyses conducted during this project can be found in the appendix, including the following:

- One year data analysis of a ROW location in North Carolina
- One-year data analysis of a grade crossing in Virginia
- Three-week data analysis of two grade crossings in Louisiana
- Automatic geolocation and data analysis of locomotive engineer-provided near-miss records from one railroad
- Forward-facing AI development and analysis
- Stopped-on-tracks solution case study in New Jersey

The results of this work and the new trespass event dataset can support FRA, railroads, and communities in better understanding trespass event behaviors and influencing factors. The developed AI system can be used to provide necessary data to justify capital investment in informed engineering, enforcement, and education solutions. This new database forms the foundation of a before/after analysis for any applied solutions at the selected locations. If applied more widely, this system can also be used to measure the effectiveness and benefit-cost ratio for applied trespass event solutions, assisting railroads and the federal government in improving public safety.

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Appendix A.
Virginia Grade Crossing Case Study

Heatmaps of trespass events at the Virginia Grade Crossing for cars, pedestrians, trucks, bicycles, buses, and total trespass events across one-hour intervals for each day of the week are depicted in Figure 40. Approximately 9.9 percent of all trespass events occurred between 4 P.M. and 5 P.M., which is the one-hour window with the highest percentage of trespass events. Car trespass events accounted for 75.6 percent and pedestrian trespass events for 22.4 percent of all trespass events.

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	4	1	4	2	5	3	16	16	22	24	7	21	12	23	23	10	18	26	26	18	14	12	7	8	322
Tuesday	1	2	6	7	7	8	20	29	25	26	14	20	9	20	28	10	16	29	28	22	11	23	4	7	372
Wednesday	2	4	4	1	0	12	12	35	31	22	0	27	7	18	14	17	18	34	35	16	16	17	4	2	348
Thursday	1	4	2	3	5	9	8	21	13	7	8	21	13	11	21	24	23	43	27	13	13	11	10	5	316
Friday	2	5	0	1	6	6	16	35	26	27	2	41	23	35	42	27	37	51	33	24	16	12	10	6	483
Saturday	2	4	2	0	2	5	11	7	32	18	18	28	11	19	29	25	9	33	18	40	13	25	9	16	376
Sunday	3	1	0	2	3	4	6	6	28	27	24	15	11	17	34	15	13	31	19	23	8	17	7	6	320
Grand Total	15	21	18	16	28	47	89	149	177	151	73	173	86	143	191	128	134	247	186	156	91	117	51	50	2,537

(a) Cars

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	1	2	5	9	6	4	3	12	6	9	10	1	6	6	5	2	1	0	0	0	88
Tuesday	0	0	0	0	1	2	3	11	7	17	7	5	3	6	6	3	6	6	5	3	4	0	2	0	97
Wednesday	0	0	0	0	0	4	10	15	17	9	1	10	0	6	7	7	6	20	9	3	0	2	0	1	127
Thursday	0	0	0	0	0	2	4	15	6	2	2	16	7	4	11	7	9	12	16	8	2	3	1	0	127
Friday	0	0	0	0	0	1	7	7	12	13	4	10	4	15	15	10	9	12	12	5	1	2	1	0	140
Saturday	0	0	1	0	0	0	3	2	18	6	9	4	5	4	6	3	2	8	11	7	3	2	1	1	96
Sunday	1	1	0	0	0	1	2	3	6	5	7	5	1	7	9	8	4	10	4	4	0	0	0	0	78
Grand Total	1	1	1	0	2	12	34	62	72	56	33	62	26	51	64	39	42	74	62	32	11	9	5	2	753

(b) Trucks

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	1	1	0	0	2	1	0	0	8
Tuesday	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	1	0	1	1	0	1	0	0	7
Wednesday	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	0	0	1	1	0	0	6
Thursday	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	3	3	1	0	0	0	0	0	10
Friday	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	1	3	4	0	0	0	0	0	11
Saturday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1	1	1	1	0	0	0	6
Sunday	0	0	0	0	0	0	0	0	1	0	0	2	0	0	1	0	0	1	1	0	0	0	0	0	6
Grand Total	0	0	0	0	1	0	1	3	1	1	0	5	1	1	4	1	6	12	8	2	4	3	0	0	54

(c) Pedestrians

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Tuesday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
Wednesday	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Thursday	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3
Friday	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	4
Saturday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sunday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grand Total	0	0	0	0	0	0	0	2	2	0	0	0	1	0	3	1	0	0	0	0	0	0	0	0	9

(d) Buses

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Tuesday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	2
Wednesday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Thursday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Friday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Saturday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sunday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grand Total	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	2

(e) Bicycles

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	4	1	4	2	7	5	21	25	28	28	10	34	19	32	33	11	25	33	31	20	17	13	7	8	418
Tuesday	1	2	6	7	8	10	23	42	32	43	21	25	12	26	38	13	23	35	34	26	15	24	6	7	479
Wednesday	2	4	4	1	0	16	22	51	48	32	1	37	7	24	21	24	24	57	44	19	17	20	4	3	482
Thursday	1	4	2	3	5	11	12	38	20	9	10	38	20	15	33	32	35	58	44	21	15	14	11	5	456
Friday	2	5	0	1	6	7	24	42	39	40	6	52	28	51	58	38	47	66	49	29	17	14	11	6	638
Saturday	2	4	3	0	2	5	14	9	50	24	27	32	16	23	37	28	11	42	30	48	17	27	10	17	478
Sunday	4	2	0	2	3	5	8	9	35	32	31	22	12	24	44	23	17	42	24	27	8	17	7	6	404
Grand Total	16	22	19	16	31	59	124	216	252	208	106	240	114	195	264	169	182	333	256	190	106	129	56	52	3,355

(f) Total

Figure 40. Virginia Trespass Events Heatmaps by Time and Day: (a) Cars; (b) Trucks; (c) Pedestrians; (d) Buses; (e) Bicycles and (f) Total Trespass Events (January 1, 2021, to January 31, 2022)

Figure 41 shows weekly and hourly temporal heatmaps of the trespass event rate per thousand at the Virginia Grade Crossing for cars, pedestrians, trucks, bicycles, buses, and total trespass events across one-hour intervals for each day of the week. All classes are less compliant during the morning peak hours.

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday	0.91	0.26	1.11	0.65	1.54	0.82	3.78	3.13	4.76	5.49	1.36	3.94	2.13	3.43	2.91	1.14	2.00	2.80	2.80	2.14	1.91	1.98	1.38	1.76
Tuesday	0.26	0.50	1.74	2.27	2.23	2.77	5.22	6.91	5.33	6.16	2.62	3.37	1.22	2.56	3.38	1.14	1.54	2.97	2.57	2.42	1.46	3.15	0.63	1.13
Wednesday	0.38	0.77	0.76	0.19	0.00	2.38	1.76	4.15	3.75	2.89	0.00	3.27	0.83	2.15	1.57	1.82	1.70	2.87	2.81	1.42	1.72	2.22	0.54	0.30
Thursday	0.20	0.83	0.42	0.72	1.07	1.85	1.39	3.34	2.44	1.43	1.41	2.81	1.65	1.26	2.64	2.35	2.10	3.72	2.35	1.24	1.46	1.65	1.96	1.33
Friday	0.61	1.81	0.00	0.38	1.99	1.53	2.74	4.85	3.42	3.20	0.23	4.55	2.21	3.24	3.81	2.22	2.99	4.32	2.95	2.29	1.74	1.48	1.57	1.11
Saturday	0.42	0.90	0.51	0.00	0.70	2.02	4.01	1.68	6.54	3.01	2.37	3.81	1.32	2.13	2.96	2.48	0.91	3.33	2.03	4.49	1.74	3.67	1.55	3.15
Sunday	0.74	0.29	0.00	0.73	1.26	1.78	2.40	1.75	7.49	6.56	5.77	3.62	2.16	2.73	6.11	2.71	2.03	4.69	2.89	3.56	1.28	2.90	1.31	1.30

(a) Cars

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday	0.00	0.00	0.00	0.00	1.55	2.27	4.33	5.98	3.80	2.06	1.34	5.26	2.72	3.57	3.51	0.36	2.19	2.08	1.95	0.91	0.53	0.00	0.00	0.00
Tuesday	0.00	0.00	0.00	0.00	1.53	2.48	2.84	9.87	4.61	10.48	3.22	1.96	1.07	1.93	1.94	1.01	1.72	1.82	1.46	1.12	1.69	0.00	1.09	0.00
Wednesday	0.00	0.00	0.00	0.00	0.00	2.50	4.33	5.47	5.91	2.97	0.30	2.83	0.00	1.82	2.19	2.05	1.73	5.16	2.34	0.89	0.00	0.84	0.00	0.52
Thursday	0.00	0.00	0.00	0.00	0.00	1.54	2.34	7.25	3.19	0.91	0.77	4.48	2.10	1.23	3.65	2.03	2.36	3.24	4.30	2.79	0.92	2.15	0.96	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.80	3.45	2.74	4.20	3.73	1.09	2.40	0.84	3.34	3.79	2.44	2.19	3.18	3.63	1.85	0.42	0.98	0.62	0.00
Saturday	0.00	0.00	1.40	0.00	0.00	0.00	3.34	1.42	11.03	2.74	3.34	1.46	1.95	1.48	2.21	1.06	0.76	2.92	4.68	3.49	1.96	1.41	0.84	1.19
Sunday	1.33	1.32	0.00	0.00	0.00	2.16	3.72	4.19	6.24	4.64	6.21	4.59	0.74	4.11	6.57	6.43	2.95	6.72	2.77	3.04	0.00	0.00	0.00	0.00

(b) Trucks

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday	0.00	0.00	0.00	0.00	40.00	0.00	0.00	0.00	0.00	0.00	0.00	31.25	29.41	0.00	0.00	0.00	26.32	21.74	0.00	0.00	23.26	20.83	0.00	0.00
Tuesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	125.00	0.00	0.00	0.00	0.00	0.00	0.00	14.93	0.00	16.95	0.00	14.93	15.63	0.00	15.63	0.00	0.00
Wednesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.87	0.00	0.00	0.00	0.00	0.00	0.00	0.00	42.25	0.00	0.00	10.87	27.78	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	14.49	0.00	0.00	0.00	17.54	0.00	0.00	0.00	10.64	53.57	78.95	13.51	0.00	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	31.25	0.00	0.00	0.00	0.00	11.90	0.00	11.11	0.00	0.00	8.62	23.62	24.54	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	12.27	0.00	0.00	10.64	10.42	8.33	16.95	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	66.67	0.00	0.00	46.51	0.00	0.00	21.28	0.00	0.00	30.30	24.39	0.00	0.00	0.00	0.00	0.00

(c) Pedestrians

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tuesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.47	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wednesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.87	12.50	0.00	0.00	0.00	0.00	0.00	5.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.25	0.00	0.00	0.00	22.73	0.00	11.24	7.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(d) Buses

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tuesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	250.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wednesday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(e) Bicycles

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday	0.75	0.21	0.94	0.55	1.79	1.09	3.85	3.66	4.35	4.38	1.35	4.42	2.40	3.39	3.00	0.94	2.11	2.69	2.59	1.86	1.83	1.67	1.08	1.38
Tuesday	0.21	0.39	1.40	1.83	2.10	2.68	4.68	7.82	5.07	7.25	2.77	2.91	1.17	2.34	3.29	1.09	1.64	2.66	2.34	2.18	1.50	2.49	0.73	0.86
Wednesday	0.28	0.58	0.57	0.14	0.00	2.39	2.37	4.46	4.22	2.95	0.09	3.11	0.57	2.04	1.71	1.86	1.69	3.59	2.65	1.27	1.38	1.97	0.42	0.34
Thursday	0.15	0.62	0.32	0.54	0.85	1.78	1.59	4.44	2.74	1.26	1.21	3.41	1.76	1.22	2.92	2.31	2.35	3.78	2.86	1.56	1.35	1.73	1.78	1.07
Friday	0.49	1.45	0.00	0.30	1.63	1.34	3.02	4.22	3.66	3.32	0.48	3.90	1.82	3.29	3.83	2.30	2.81	4.17	3.33	2.16	1.44	1.36	1.36	0.89
Saturday	0.34	0.74	0.65	0.00	0.58	1.63	3.81	1.60	7.61	2.91	2.60	3.14	1.45	1.95	2.91	2.11	0.87	3.28	2.65	4.34	1.88	3.25	1.41	2.85
Sunday	0.82	0.47	0.00	0.61	1.04	1.83	2.62	2.15	7.42	6.12	5.83	4.16	1.85	3.00	6.29	3.36	2.17	5.16	2.97	3.45	1.06	2.39	1.10	1.06

(f) Total

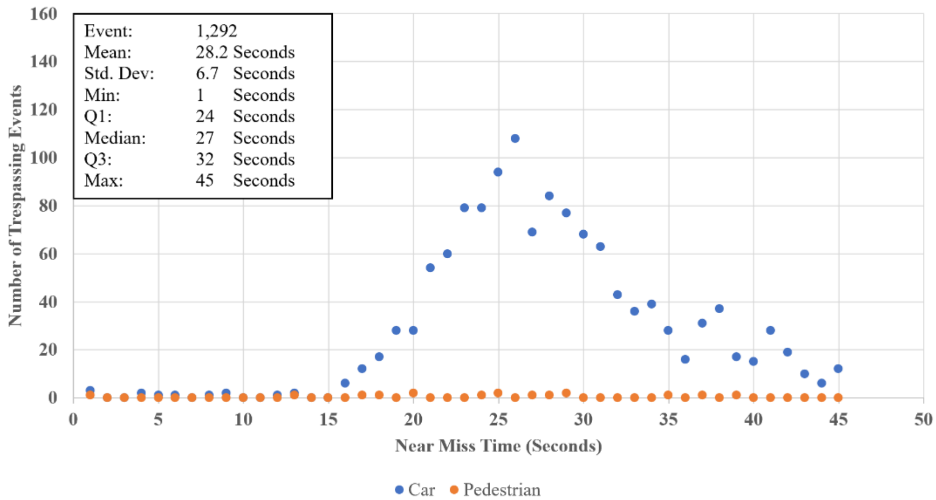
Figure 41. Virginia Trespass Events Rate Per Thousand Heatmaps by Time and Day: (a) Cars; (b) Trucks; (c) Pedestrians; (d) Buses; (e) Bicycles; and (f) Total Trespass Events (January 1, 2021, to January 31, 2022)

Table 8 shows the factor analysis of five distinct types of trespass events at the Virginia Grade Crossing. During the study period, the total car, pedestrian, truck, bicycle, and bus traffic was collected, and the average daily traffic was calculated by class, indicating that bicycles have the largest trespass event rate per thousand, followed by pedestrian trespass events. Other types of trespass events (e.g., car, truck, and bus) have lower trespass event rates per thousand.

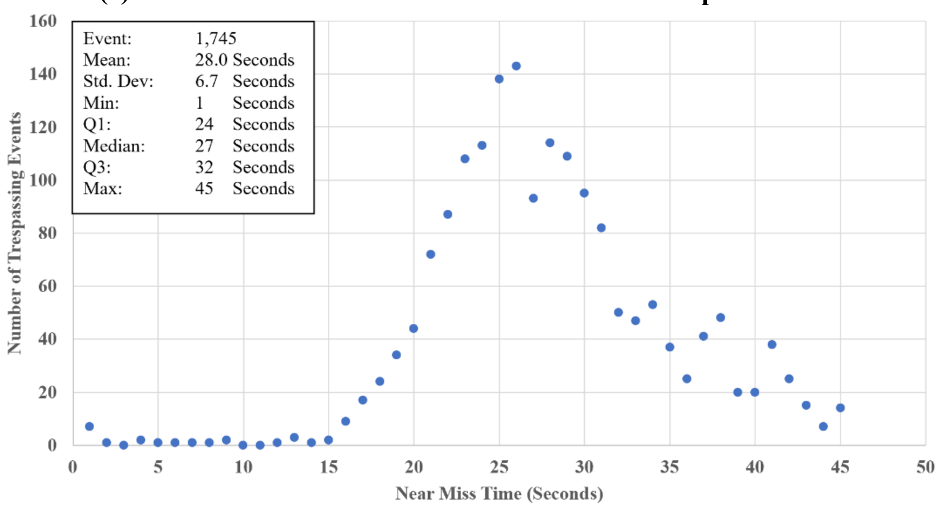
Table 8. Virginia Grade Crossing Total Trespass Event Traffic Exposure by Class

Class	Total Traffic	Total Trespass Events	Trespass Event Rate Per Thousand
Car	1,090,963	2,537	2.33
Truck	336,470	753	2.24
Pedestrian	9,325	54	5.79
Bicycle	279	2	7.17
Bus	7,435	9	1.21
Total	1,444,472	3,355	2.32

The near-miss analysis of the trespass events for cars and pedestrians and total trespass events at the Virginia Grade Crossing is shown in Figure 42. In this figure, each dot represents the total number of trespass events that occurred at specific near-miss times. The near-miss distribution of all types of trespass events indicates an average near-miss time of 28 seconds.



(a) Near-Miss Distribution for Car + Pedestrian Trespass Events



(b) Near-Miss Distribution for All Trespass Events

Figure 42. Virginia Grade Crossing Near-miss Distribution: (a) Car + Pedestrian and (b) All Trespass Events (January 1, 2021, to January 31, 2022)

Heatmaps were generated for all trespass events at the Virginia Grade Crossing in the camera's field of view (Figure 43) and from a transformed aerial view (Figure 44).

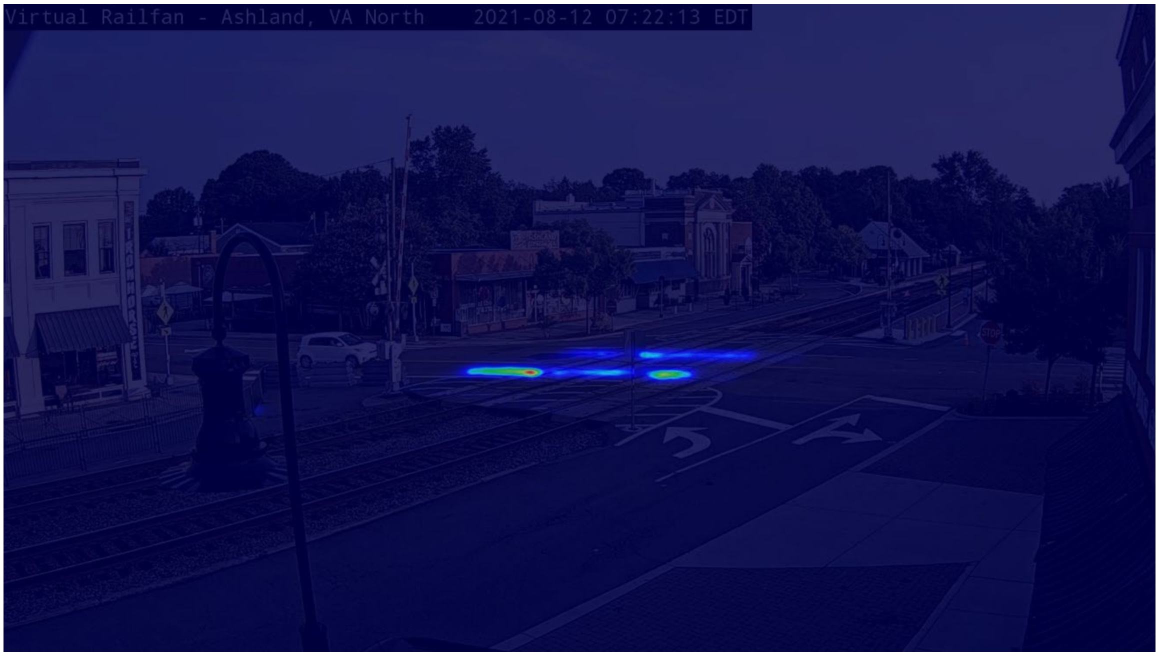
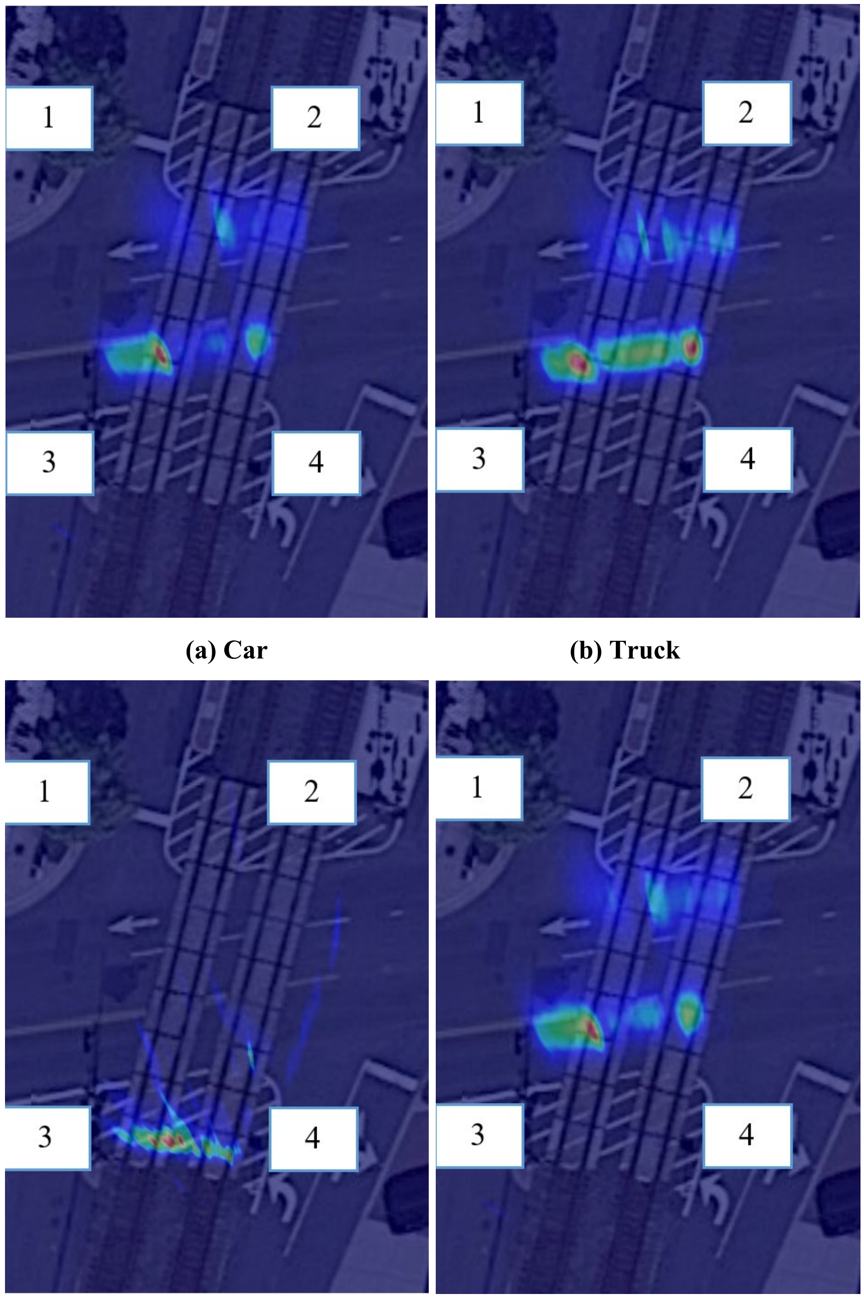


Figure 43. Grade Crossing Violator Spatial Heatmap for All Classes with Origin and Destination Zones (January 1, 2021, to January 31, 2022)



(a) Car **(b) Truck**

(c) Pedestrian **(d) Total**

Figure 44. Virginia Grade Crossing Aerial-view Heatmap of Grade Crossing Trespass Events: (a) Cars; (b) Trucks; (c) Pedestrians; and (d) Total

Appendix B.
North Carolina Right-of-Way, South Camera View Case Study

Heatmaps of trespass events from the North Carolina ROW South Camera View for cars, pedestrians, trucks, bicycles, buses, and total trespass events across one-hour intervals for each day of the week are depicted in Figure 45. Approximately 9.3 percent of all trespass events occurred between 11 A.M. and 12 A.M., which is the one-hour window with the highest percentage of trespass events. Pedestrian trespass events accounted for 99.8 percent of all trespass events.

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	1	4	6	16	15	22	28	18	23	21	15	11	25	17	10	9	14	8	4	0	267
Tuesday	1	0	0	0	0	0	10	7	27	23	23	20	22	24	12	15	14	26	13	6	17	8	4	1	273
Wednesday	2	1	0	3	0	2	4	13	18	18	14	30	32	14	14	15	17	11	12	11	10	8	4	3	256
Thursday	0	1	0	0	1	1	7	10	20	19	23	18	27	12	4	8	28	16	15	21	13	6	2	5	257
Friday	1	1	1	0	2	5	8	15	10	23	24	30	43	22	18	15	25	19	12	16	12	16	6	5	329
Saturday	5	1	0	3	1	1	0	2	14	25	10	21	13	17	20	26	20	17	15	15	12	8	3	5	254
Sunday	2	3	0	0	1	2	2	2	5	7	5	9	13	12	23	26	14	25	16	19	18	10	4	2	220
Grand Total	11	7	1	6	6	15	37	65	109	137	127	146	173	122	106	116	143	131	93	97	96	64	27	21	1,856

(a) Pedestrians

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Tuesday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wednesday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Thursday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Friday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Saturday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sunday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
Grand Total	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	2

(b) Bicycles

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Tuesday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wednesday	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Thursday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Friday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Saturday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sunday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grand Total	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1

(c) Cars

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	1	4	6	16	15	22	28	18	23	21	15	11	25	17	10	9	14	8	4	0	267
Tuesday	1	0	0	0	0	0	10	7	27	23	23	20	22	24	12	15	14	26	13	6	17	8	4	1	273
Wednesday	2	1	0	3	0	2	4	13	18	18	14	31	32	14	14	15	17	11	12	11	10	8	4	3	257
Thursday	0	1	0	0	1	1	7	10	20	19	23	18	27	12	4	8	28	16	15	21	14	6	2	5	258
Friday	1	1	1	0	2	5	8	15	10	23	24	30	43	22	18	15	25	19	12	16	12	16	6	5	329
Saturday	5	1	0	3	1	1	0	2	14	25	10	21	13	17	20	26	20	17	15	15	12	8	3	5	254
Sunday	2	3	0	0	1	2	2	2	5	7	5	9	13	12	23	26	14	25	17	19	18	10	4	2	221
Grand Total	11	7	1	6	6	15	37	65	109	137	127	147	173	122	106	116	143	131	94	97	97	64	27	21	1,859

(d) Total

Figure 45. North Carolina ROW South Camera View Trespass Event Heatmaps by Time and Day: (a) Cars; (b); Pedestrians (c) Bicycles; (d) Total Trespass Events (January 1, 2021, to December 31, 2021)

The near-miss analysis of the trespass events for cars and pedestrians and total trespass events from the North Carolina ROW South Camera View is shown in Figure 46. In this figure, each dot represents the total number of trespass events that occurred at specific near-miss times. The near-miss distribution of all types of grade crossing trespass events indicates an average near-miss time of 26.9 seconds.

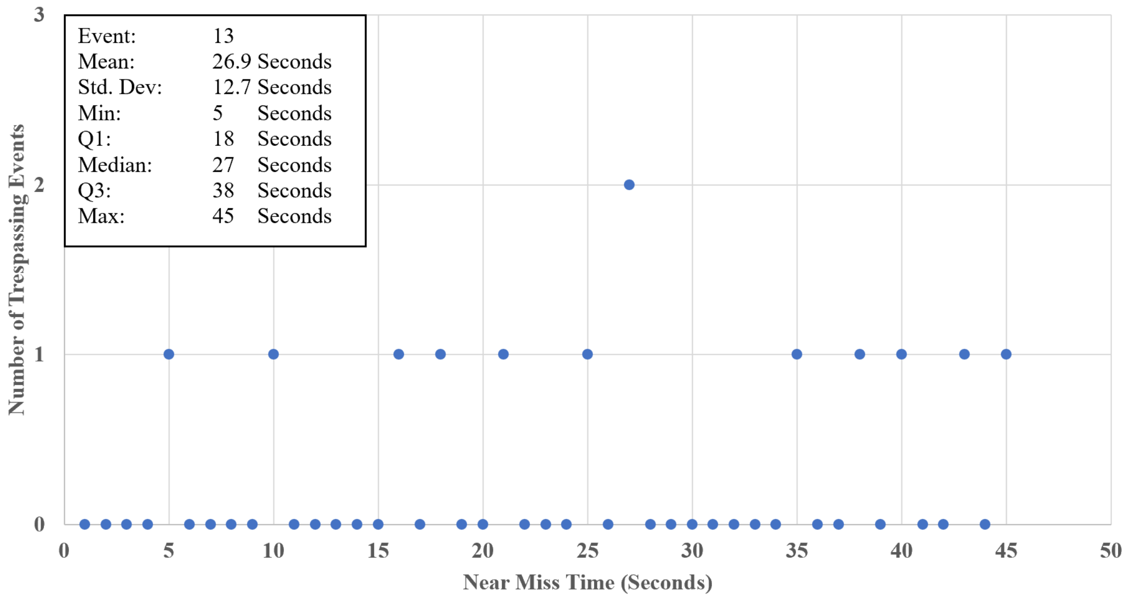


Figure 46. North Carolina ROW South Camera View Near-miss Distribution (January 1, 2021, to December 31, 2021)

Figure 47 shows an example of a trespass event (red box) at the North Carolina ROW South Camera View.

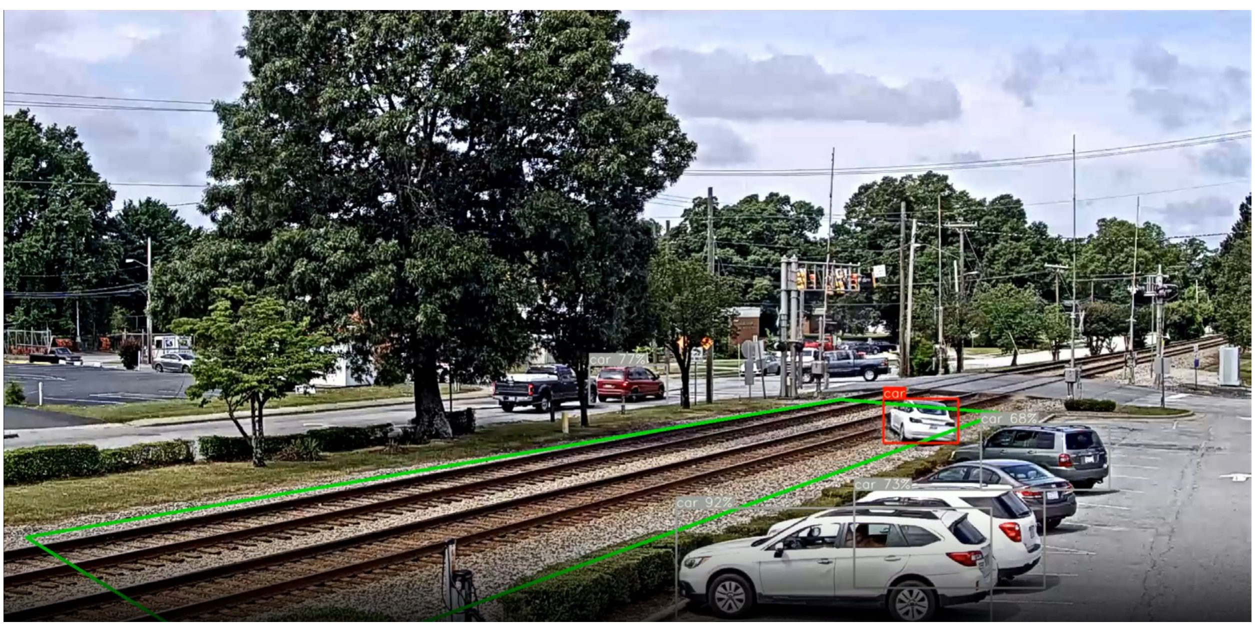


Figure 47. North Carolina ROW South Camera View Car Trespass Event

Heatmaps were generated for all trespass events at the North Carolina ROW South Camera View in the camera's field of view (Figure 48) and from a transformed aerial view (Figure 49).

Figure 48. North Carolina ROW South Camera View Trespass Event Spatial Heatmap for All Classes with Origin and Destination Zones (January 1, 2021, to December 31, 2021)

Figure 49. North Carolina ROW South Camera View Aerial-view Trespass Spatial Heatmap for All Classes with Origin and Destination Zones (January 1, 2021, to December 31, 2021)

Appendix C.
Louisiana Multi-lane Highway Grade Crossing Case Study

Heatmaps of trespass events at the Louisiana Multi-lane Highway Grade Crossing for cars, pedestrians, trucks, buses, and total trespass events across one-hour intervals for each day of the week are depicted in Figure 50. Data was collected using a battery-powered camera system; not all days and hours were captured continuously, resulting in gaps in the heatmaps.

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday																									0
Tuesday																									0
Wednesday										0	0	0	0	1	53	40	25	0	0	0	0	0	0	0	119
Thursday	0	0	0	7	5	0	8	0	0	0	0	0	0	0	0	91	81	0	0	30	0	0	0	0	222
Friday	1	0	0	0	0	0	7	11	0	0	12	0	0	0	0	52	60	0	0	0	3	0	0	0	146
Saturday	0	0	0	0	2	0	7	0	0	0	0	0	0	0	0	49	0	0	5	11	0	0	6	0	80
Sunday	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	3	0								9
Grand Total	1	0	0	7	7	0	28	11	0	0	12	0	0	1	53	235	166	0	5	41	3	0	6	0	576

(a) Cars

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday																									0
Tuesday																									0
Wednesday										0	0	0	0	1	16	24	3	0	0	0	0	0	0	0	44
Thursday	0	0	0	1	0	0	4	0	0	0	0	0	0	0	0	40	22	0	0	4	0	0	0	0	71
Friday	0	0	0	0	0	0	0	5	0	0	6	0	0	0	0	20	20	0	0	0	0	0	0	0	51
Saturday	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	10	0	0	3	1	0	0	0	0	15
Sunday	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0								2
Grand Total	0	0	0	1	0	0	6	5	0	0	6	0	0	1	16	95	45	0	3	5	0	0	0	0	183

(b) Trucks

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday																									0
Tuesday																									0
Wednesday										0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Thursday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Friday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	2
Saturday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sunday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								0
Grand Total	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	2

(c) Buses

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday																									0
Tuesday																									0
Wednesday										0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
Thursday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Friday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Saturday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sunday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								0
Grand Total	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1

(d) Pedestrians

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday																									0
Tuesday																									0
Wednesday										0	0	0	0	2	69	65	28	0	0	0	0	0	0	0	164
Thursday	0	0	0	8	5	0	12	0	0	0	0	0	0	0	0	131	103	0	0	34	0	0	0	0	293
Friday	1	0	0	0	0	0	7	16	0	0	18	0	0	0	0	74	80	0	0	0	3	0	0	0	199
Saturday	0	0	0	0	2	0	8	0	0	0	0	0	0	0	0	59	0	0	8	12	0	0	6	0	95
Sunday	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	4	0								11
Grand Total	1	0	0	8	7	0	34	16	0	0	18	0	0	2	69	333	211	0	8	46	3	0	6	0	762

(e) Total

Figure 50 Louisiana Multi-lane Highway Grade Crossing Trespass Events Heatmaps by Time and Day: (a) Cars; (b); Trucks (c) Buses; (d) Pedestrians; and (e) Total Trespass Events (June 9, 2021, to June 26, 2021)

Figure 51 shows weekly and hourly temporal heatmaps of the trespass event rate per thousand for cars, pedestrians, trucks, buses, and total trespass events across one-hour intervals for each day of the week. All classes are less compliant during the afternoon from 3 P.M. to 4 P.M.

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday																								
Tuesday																								
Wednesday										0.00	0.00	0.00	0.00	0.15	7.48	4.76	2.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	28.69	9.94	0.00	1.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	12.88	11.36	0.00	0.00	7.93	0.00	0.00	0.00	0.00
Friday	2.48	0.00	0.00	0.00	0.00	0.00	2.17	1.98	0.00	0.00	2.26	0.00	0.00	0.00	0.00	6.50	7.13	0.00	0.00	0.00	0.76	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	9.09	0.00	4.78	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	17.45	0.00	0.00	1.20	2.77	0.00	0.00	6.25	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	8.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.68	0.00							

(a) Cars

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday																								
Tuesday																								
Wednesday										0.00	0.00	0.00	0.00	0.44	7.64	10.89	1.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	25.64	0.00	0.00	2.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	16.54	10.70	0.00	0.00	6.00	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.37	0.00	0.00	2.52	0.00	0.00	0.00	0.00	8.70	8.62	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	2.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	15.77	0.00	0.00	3.22	1.87	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	6.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.29	0.00							

(b) Trucks

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday																								
Tuesday																								
Wednesday										0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	181.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00							

(c) Buses

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday																								
Tuesday																								
Wednesday										0.00	0.00	0.00	0.00	0.00	0.00	90.91	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00							

(d) Pedestrians

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday																								
Tuesday																								
Wednesday										0.00	0.00	0.00	0.00	0.23	7.50	6.12	2.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	28.27	9.23	0.00	1.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	13.77	11.19	0.00	0.00	7.64	0.00	0.00	0.00	0.00
Friday	2.38	0.00	0.00	0.00	0.00	0.00	1.52	2.09	0.00	0.00	2.34	0.00	0.00	0.00	0.00	7.18	7.44	0.00	0.00	0.00	0.69	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	7.66	0.00	4.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	16.91	0.00	0.00	1.57	2.66	0.00	0.00	6.13	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	7.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.79	0.00							

(e) Total

Figure 51. Louisiana Multi-lane Highway Grade Crossing Trespass Event Rate Per Thousand Heatmaps by Time and Day: (a) Cars; (b); Trucks (c) Buses; (d) Pedestrians; and (e) Total Trespass Events (June 9, 2021, to June 26, 2021)

Table 9 shows the factor analysis of four distinct types of trespass events. During the study period, the total car, pedestrian, truck, and bus traffic was collected, and the average daily traffic was calculated by class, indicating that buses had the largest trespass event rate per thousand, although this is likely due to a small sample size. Other types of trespass events (e.g., car, truck) had low trespass event rates per thousand.

Table 9. Louisiana Multi-lane Highway Grade Crossing Total Trespass Events Traffic Exposure by Class

Class	Total Traffic	Total Trespass Events	Trespass Events Rate Per Thousand
Car	365,832	576	1.57
Truck	103,234	183	1.77
Bus	340	2	5.88
Pedestrian	506	1	1.98
Total	469,912	762	1.62

The near-miss analysis of trespass events is shown in Figure 52. In this figure, each dot represents the total number of trespass events that occurred at specific near-miss times. The near-miss distribution of all types of trespass events indicates an average near-miss time of 29.1 seconds.

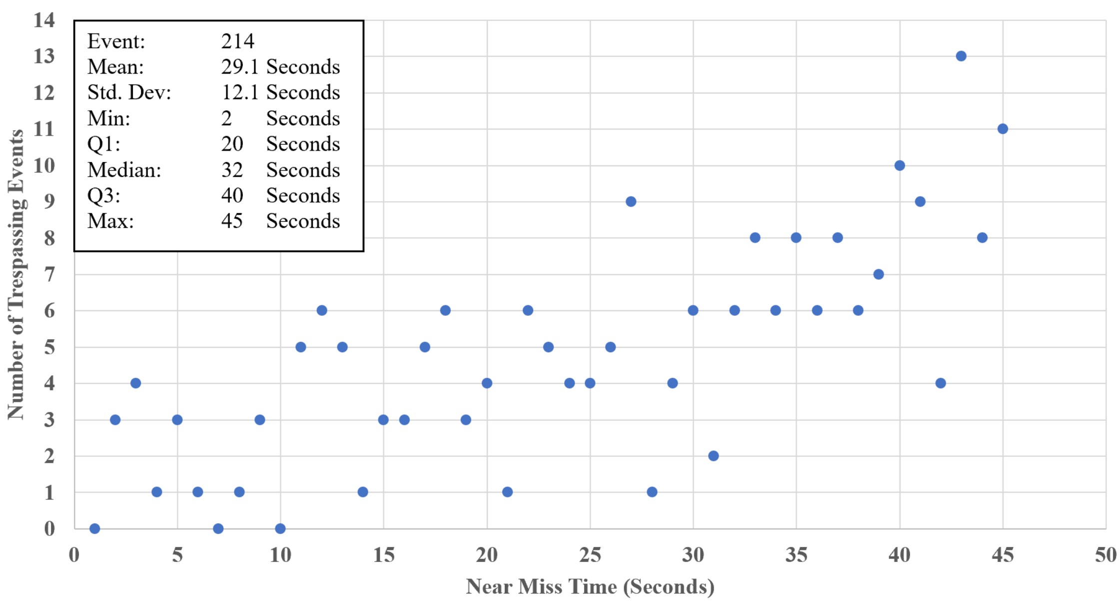


Figure 52. Louisiana Multi-lane Highway Grade Crossing Near-miss Distribution of All Trespass Events (June 9, 2021, to June 26, 2021)

Heatmaps were generated for all trespass events at the Louisiana Multi-lane Highway Grade Crossing in the camera's field of view (Figure 53) and from a transformed aerial view (Figure 54).

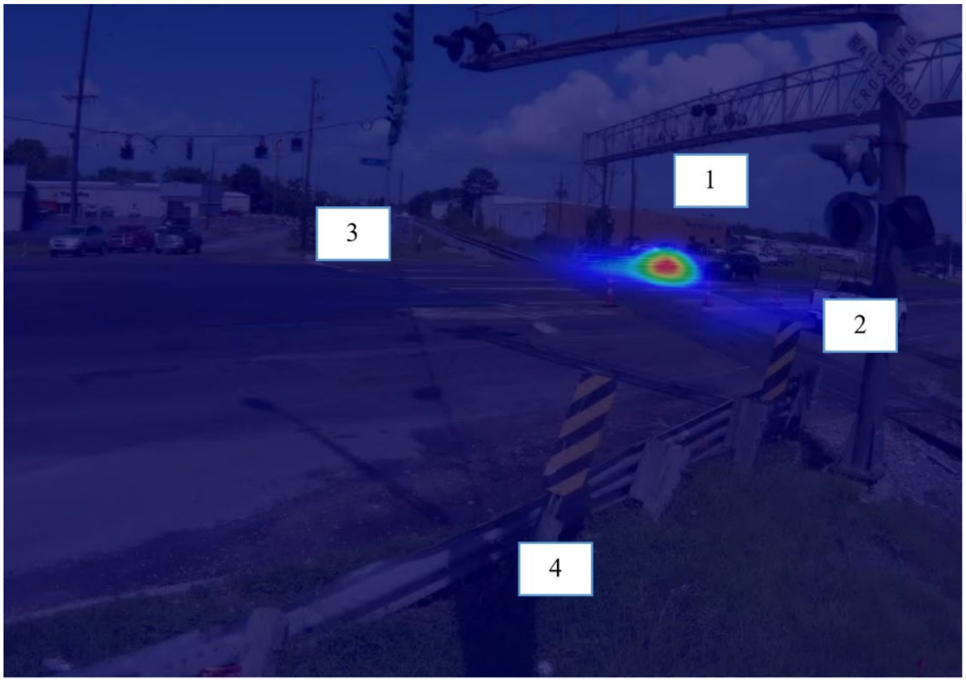


Figure 53. Louisiana Multi-lane Highway Grade Crossing Violator Spatial Heatmap for All Classes with Origin and Destination Zones (June 9, 2021, to June 26, 2021)

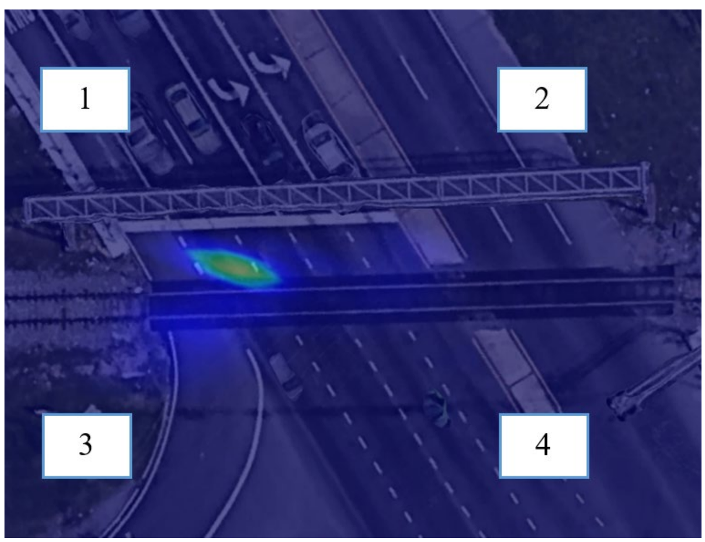


Figure 54. Louisiana Multi-lane Highway Grade Crossing Aerial-view Heatmap

Appendix D.
Louisiana Local Road Grade Crossing Case Study

Heatmaps of trespass events at the Louisiana Local Road Grade Crossing for cars, trucks, and total trespass events across one-hour intervals for each day of the week are depicted in Figure 55. Gaps in the heatmaps are caused by time to uninstall, recharge, and redeploy the battery-powered camera system.

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4										4
Tuesday																									0
Wednesday										0	0	0	0	1	0	0	16	0	0	0	0	0	0	0	17
Thursday	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	11
Friday	0	0	0	0	0	0	48	7	0	0	5	1	0	0	0	4	0	0	0	0	0	0	0	0	65
Saturday	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
Sunday	0	0	0	0	0	3	0	0	0	0	0	0	0	0	4	0	12	0	0	0	0	0	1	1	21
Grand Total	0	0	0	0	5	10	48	7	0	0	5	1	0	1	8	4	28	0	0	6	0	0	1	1	125

(a) Cars

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0										0
Tuesday																									0
Wednesday										0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	3
Thursday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	4
Friday	0	0	0	0	0	0	9	1	0	0	2	1	0	0	0	1	0	0	0	0	0	0	0	0	14
Saturday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sunday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grand Total	0	0	0	0	0	0	9	1	0	0	2	1	0	1	0	1	2	0	0	4	0	0	0	0	21

(b) Trucks

	Hour of Day																								
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Grand Total**
Monday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4										4
Tuesday																									0
Wednesday										0	0	0	0	2	0	0	18	0	0	0	0	0	0	0	20
Thursday	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	15
Friday	0	0	0	0	0	0	57	8	0	0	7	2	0	0	0	5	0	0	0	0	0	0	0	0	79
Saturday	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
Sunday	0	0	0	0	0	3	0	0	0	0	0	0	0	0	4	0	12	0	0	0	0	0	1	1	21
Grand Total	0	0	0	0	5	10	57	8	0	0	7	2	0	2	8	5	30	0	0	10	0	0	1	1	146

(c) Total

Figure 55 Louisiana Local Road Grade Crossing Trespass Events Heatmaps by Time and Day: (a) Cars; (b) Trucks and (c) Total Trespass Events (June 9, 2021, to June 28, 2021)

Figure 56 shows weekly and hourly temporal heatmaps of the trespass event rate per thousand for cars, trucks, and total trespass events across one-hour intervals for each day of the week. All classes are less compliant during the morning hours.

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.93									
Tuesday																								
Wednesday										0.00	0.00	0.00	0.00	0.39	0.00	0.00	5.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	74.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.50	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	166.09	7.70	0.00	0.00	2.43	0.38	0.00	0.00	0.00	1.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	44.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	26.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.78	0.00	10.04	0.00	0.00	0.00	0.00	0.00	3.70	4.81

(a) Cars

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00									
Tuesday																								
Wednesday										0.00	0.00	0.00	0.00	1.63	0.00	0.00	3.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	13.03	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	78.95	3.57	0.00	0.00	3.32	1.18	0.00	0.00	0.00	1.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(b) Trucks

	Hour of Day																							
Day of Week	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Monday	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.60									
Tuesday																								
Wednesday										0.00	0.00	0.00	0.00	0.62	0.00	0.00	5.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.00	67.57	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.91	0.00	0.00	0.00	0.00
Friday	0.00	0.00	0.00	0.00	0.00	0.00	141.44	6.68	0.00	0.00	2.61	0.57	0.00	0.00	0.00	1.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturday	0.00	0.00	0.00	0.00	0.00	38.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sunday	0.00	0.00	0.00	0.00	0.00	24.39	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.32	0.00	8.30	0.00	0.00	0.00	0.00	0.00	3.70	4.76

(c) Total

Figure 56. Louisiana Local Road Grade Crossing Trespass Event Rate Per Thousand Heatmaps by Time and Day: (a) Cars; (b) Trucks; and (c) Total Trespass Events (June 9, 2021, to June 28, 2021)

Table 10 shows the factor analysis of two distinct types of grade-crossing violators. During the study period, the total car and truck traffic was collected, and the average daily traffic was calculated by class.

Table 10. Louisiana Local Road Grade Crossing Total Trespass Events Traffic Exposure by Class

Class	Total Traffic	Total Trespass Events	Trespass Event Rate Per Thousand
Car	142,831	125	0.88
Truck	30,435	21	0.69
Total	173,266	146	0.84

The near-miss analyses of the trespass events for cars and pedestrians and total trespass events are shown in Figure 57. In this figure, each dot represents the total number of trespass events that occurred at specific near-miss times. The near-miss distribution of all types of trespass events indicates an average near-miss time of 25.0 seconds.

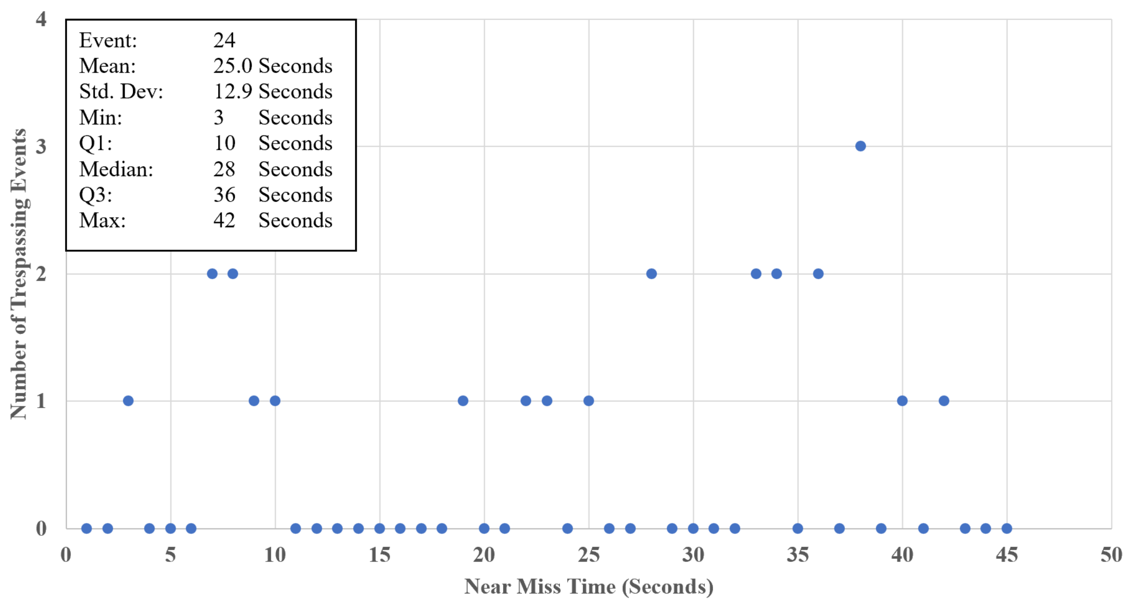


Figure 57. Louisiana Local Road Grade Crossing Near-miss Distribution of All Grade Crossing Trespass Events (June 9, 2021, to June 28, 2021)

Heatmaps were generated for all trespass events in the camera's field of view (Figure 58) and from a transformed aerial view (Figure 59).

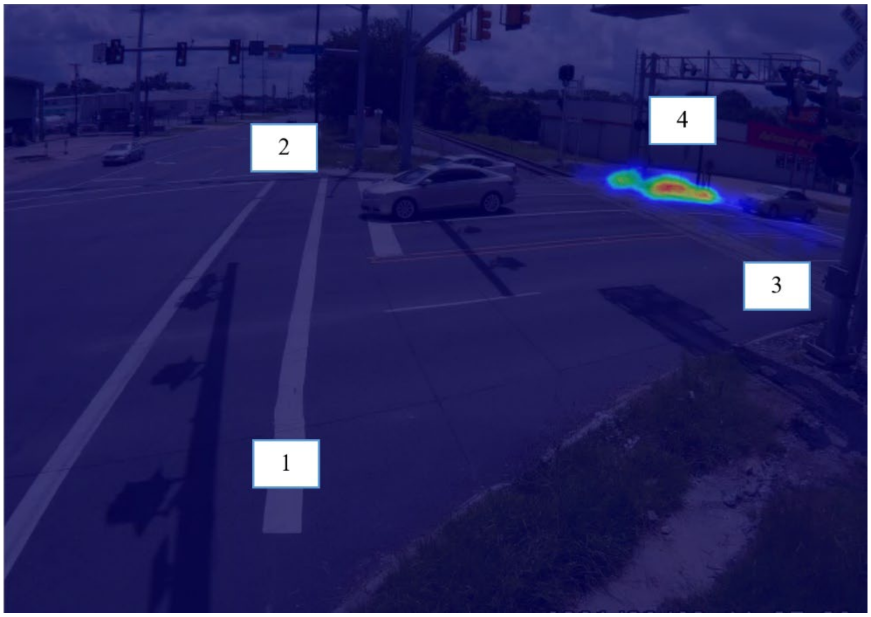


Figure 58. Louisiana Local Road Grade Crossing Violator Spatial Heatmap for All Classes with Origin and Destination Zones (June 9, 2021, to June 28, 2021)

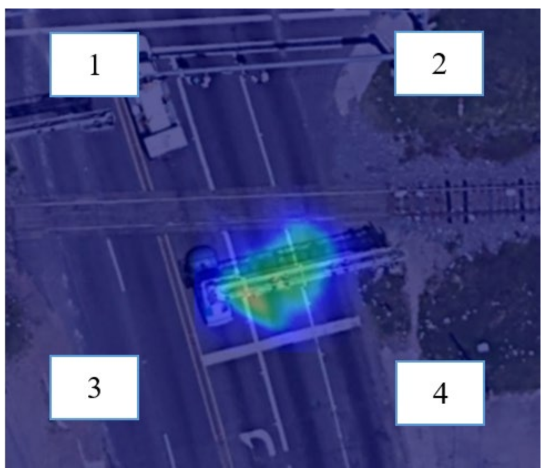


Figure 59. Louisiana Local Road Grade Crossing Aerial-view Heatmap of Total Grade Crossing Trespass Events (June 9, 2021, to June 28, 2021)

Appendix E.
Trespasser Near-miss Visualization

Near-miss Data

In this project, researchers investigated automatically geolocating and visualizing near-miss trespassing records provided by one railroad. These records were originally obtained through reports provided by locomotive engineers to the railroad's safety department and aggregated into an Excel sheet. Data was provided from 2017 to 2022. Exact records are not shown due to a confidentiality agreement established between the railroad and the research team. Table 11 shows the relevant near-miss database fields shared by the collaborator.

Table 11. Near-miss Database Fields

Data	Data Types
Date	
Day of Week	
Time	
District	
Line	
ST/M.P.	Cross Street or Milepost
Nearest Station	
City	
Violator Type	Motorist, Pedestrian, Commuter(s)
Vehicle Details	License Plate #, State, Make, Model, Color
Vehicle Type	Bicycle, Bus, Car, Van, Construction, Emergency, Taxi, Motorcycle, Truck, SUV
Warning Devices Activated	Yes or No
Driver Action	1. Did not stop 2. Stopped before crossing then proceeded 3. Stopped on or fouled tracks then proceeded
Tresp/Details-Race	
Age	Adult or Juvenile
Gender	
Tresp/Activity:	1. Crossed in front of the train 2. Group gathering around the crossing/platform 3. Playing chicken/other 4. Walking/running down tracks 5. Went around, under, or through crossing protection 6. Standing on or near the tracks

Near-miss Processing and Geolocation

A shape file of the rail agency's lines and stations was provided to geolocate each near-miss for visualization. However, geolocation information was not consistent in the provided datasets. Engineer reports provided either the milepost, nearest cross street, or nearest station where a trespasser was identified. To generate the near-miss shapefile, the following procedure was developed.

Data for which mileposts were provided:

1. The system parses a near-miss record.
2. The system locates the line and milepost in the shape file.
3. The system records the GPS coordinates of the near-miss in an output Excel file.

Data for which only cross streets were provided:

1. The system parses a near-miss record.
2. The system locates the line in the provided shape file.
3. The system locates the closest matching cross street in a publicly available street shape file.
4. The system finds the intersection between the line and the matching cross street.
5. The system records the GPS coordinates of the near-miss in an output Excel file.

Data for which only the nearest station was provided:

1. The system parses a near-miss record.
2. The system locates the line and nearest station in the shape file.
3. The system records the GPS coordinates of the near-miss in an output Excel file.

Additionally, data fields were not entered into the system in a consistent format. For example, a milepost could be represented by an integer (1), double (1.25), or as text (MP 1.25). Furthermore, cross streets could be represented in a variety of formats (e.g., "Main Street," "Main St.," "Main St," etc.). Relational libraries and scripts were developed and incorporated into the system to automatically clean and standardize key fields for visualization.

Near-miss Visualization

The system processes the near-misses and automatically displays them on a web dashboard. The system can also take already processed and cleaned data and visualize them immediately. A conceptual example of geolocated near-misses can be seen in Figure 43. A conceptual example of trespasser demography can be seen in Figure 61. A conceptual example of a trespasser temporal heatmap can be seen in Figure 62. A conceptual example of vehicle trespasser types can be seen in Figure 43.

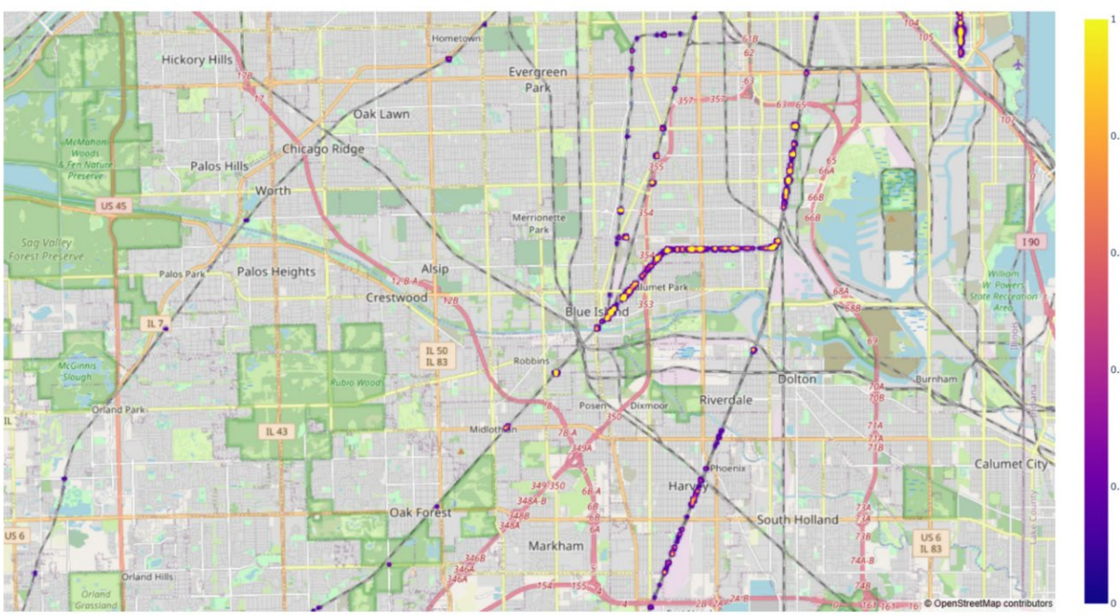


Figure 60. Conceptual Example Near-miss Spatial Heatmap

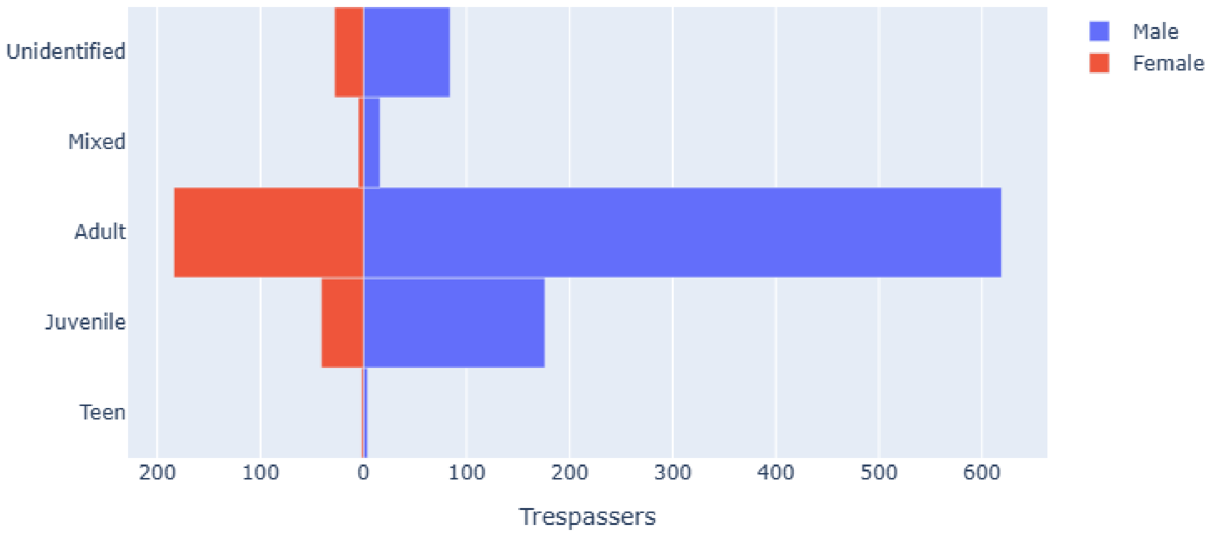


Figure 61. Conceptual Example Trespasser Demography

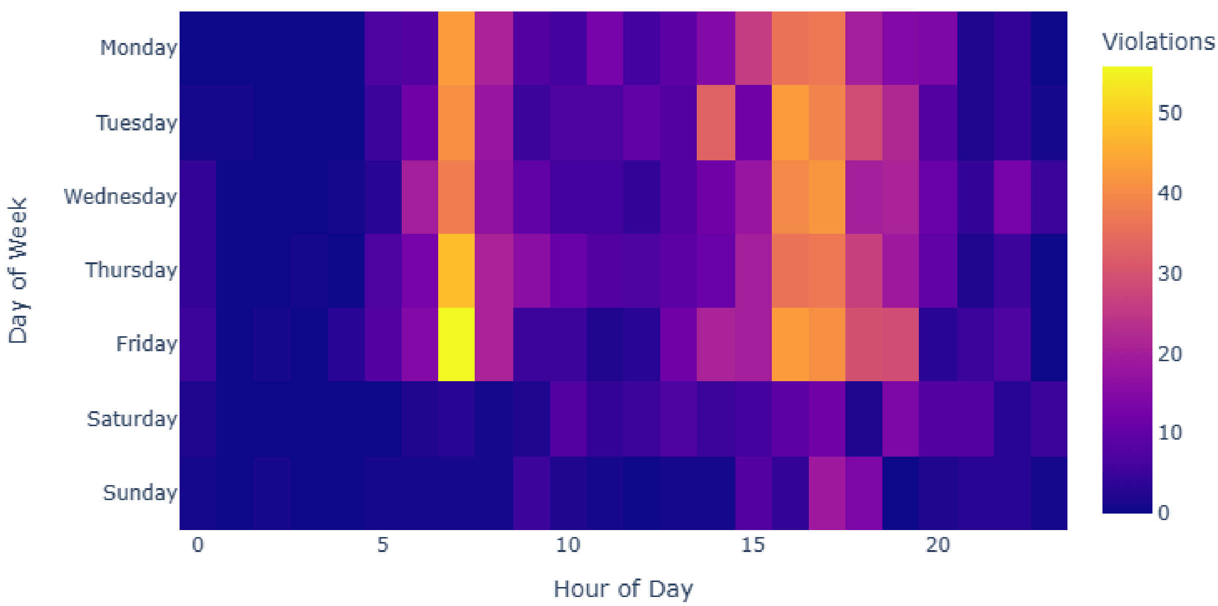


Figure 62. Conceptual Example Trespasser Temporal Heatmap

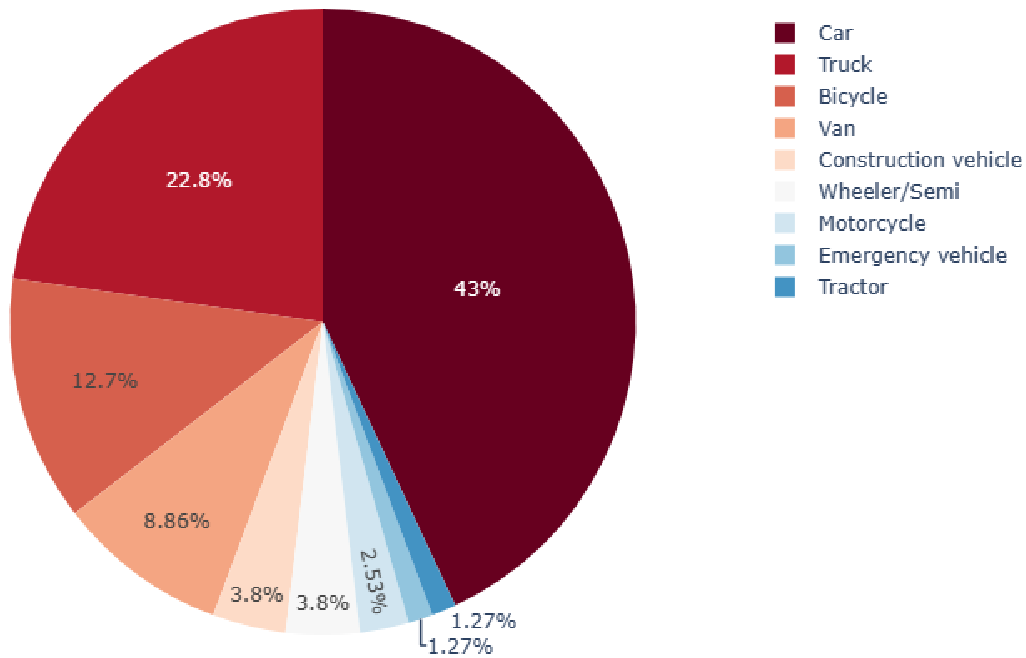


Figure 63. Conceptual Example Vehicle Trespass Type Breakdown

Abbreviations and Acronyms

ACRONYM	DEFINITION
AI	Artificial Intelligence
AP	Average Precision
API	Application Program Interface
CCTV	Closed Circuit Television
COCO	Common Objects in Context
DCNN	Deep Convolutional Neural Networks
FPS	Frame per Second
FRA	Federal Railroad Administration
GTCD	Volpe Center's Grade Crossing Trespassing Detection Software
HSV	Hue Saturation Value
IOU	Intersection Over Union
IP	Internet Protocol
mAP	Mean Average Precision
MOTA	Multiple Object Tracking Accuracy
NJT	New Jersey Transit
R-CNN	Region-based Convolutional Neural Network
RISE	Rail Information Sharing Environment
ROI	Region of Interest
ROW	Right-of-Way
RPN	Region Proposal Network
SORT	Simple Online Realtime Tracking
VOC	Pascal Visual Object Classes
YOLO	You Only Look Once