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Artificial Intelligence-Aided Grade Crossing Safety Violation Detection Methodology and a Case Study in New Jersey

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Abstract

Fatalities at grade crossings accounted for an average of 33% of all railroad industry fatalities occurring in the past 10 years. As road traffic increases and high-speed rail deployments become more common in the United States, the number of fatalities is expected to remain a concern. Railroads have tackled this challenge through a combination of engineering, education, and enforcement campaigns. One of these efforts has been the increased deployment of security cameras throughout railroad networks. These video sources allow for the collection of big data to better understand grade crossing violation behaviors. However, monitoring these video feeds and extracting useful information requires prohibitive amounts of manual labor. This research utilizes state-of-the-art vision-based artificial intelligence (AI) techniques to record, recognize, and understand railroad video data in real time. This system's understanding of active grade crossing violations helps to develop precise long-term grade crossing violation prevention strategies. This study explains how this AI-aided algorithm is used to monitor 1 year's worth of violations at an active grade crossing in New Jersey and provides an overview of the observed trends. These data can be used to develop better engineering enforcement and education strategies for the mitigation of active grade crossing violations.

Keywords

public transportation, rail transit systems, commuter rail, rail, highway/rail grade crossings

Fatalities at grade crossings accounted for an average of 33% of all fatalities in the railroad industry in the past 10 years (*1*). The significance of this issue has been emphasized by Federal Railroad Administration (FRA) Administrator Amit Bose, who stated 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" (*2*). This trend exists for railroads across the United States. New Jersey Transit's (NJT) 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" (*3*).

Railroads have worked to tackle this challenge through a combination of engineering, education, and enforcement campaigns. One result of these efforts has been the increased deployment of security cameras throughout railroad networks. For example, 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" (*3*). These cameras are a source of big data that can be used to better understand grade crossing violation behaviors. However, monitoring these video feeds and extracting useful information from them requires prohibitive amounts of manual labor.

Concurrent with the challenge of limited resources to study grade crossing violations in detail is the constant and rapid development of video-based artificial

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intelligence (AI) algorithms (Mask Regional Convolutional Neural Network (Mask R-CNN) (*4*), You Only Look Once (YOLO) (*5*), etc.) which can read, recognize, and understand what is happening in video feeds. The combination of the intransigent grade crossing violation challenge, the continued deployment of railroad video infrastructure, and the rapid development of vision-based AI presents the research gap this paper aims to fill. This research utilized state-of-the-art vision-based AI to watch, recognize, and understand railroad big video data in real time to understand grade crossing violations and to develop precise engineering, enforcement, and education strategies.

The paper is organized as follows. The first section describes the paper's objectives. The literature review section explores current trends in collecting and analyzing grade crossing violation data. The framework section describes the proposed AI-aided framework to analyze video of grade crossing violations. The case study section describes the data and trends of the analyzed grade crossing, followed by the results section which shows the detailed output. Finally, the last section offers the paper's conclusions.

Research Objectives

The data and analyses presented in this research cover one grade crossing in New Jersey. The video feed from this crossing was analyzed for 1 year by the developed AI system, populating a database with violation data for further analysis.

This research represents the first long-term study of grade crossing safety violations of its kind and accomplishes the following goals:

- Develop an AI framework for grade crossing violation detection and data gathering.
- Evaluate the effectiveness of an AI at recognizing and collecting data on grade crossing violations.
- Understand the seasonal and long-term trends of grade crossing violations as the first long-term continuous study of a crossing of its kind.
- Determine engineering, enforcement, and education recommendations for the grade crossing based on data analyses.

Literature Review

A literature review was conducted to understand current practices for collecting and analyzing grade crossing violation data in the railroad industry. A grade crossing is defined by the FRA as "a location where a public or private road, street, sidewalk or pathway, intersects railroad tracks at the same level" (*6*). In the context of this research, grade crossing violations are defined as unauthorized people or vehicles entering an active signalized grade crossing after it has been activated.

Fatalities at grade crossings account for an average of 33% of all fatalities in the railroad industry occurring in the past 10 years (*1*). In addition to the lives lost, there are scheduling impacts, delays, and other unaccounted costs, which further increase the significance of this national issue. While the number of crashes and fatalities at grade crossings is significant, it is the result of a series of precursory risky behaviors. Research performed by Zaman et al. (*7*, *8*) and Zhang et al. (*9*, *10*) from 2018 to 2022 has demonstrated that there are many more grade crossing violation incidents which do not result in accidents. However, each of these events has the potential to result in a fatality. Analyzing these violation events contributes to the development of mitigation strategies.

Grade crossing violation data are mostly collected and analyzed manually. Hellman et al. reviewed video data to evaluate the effectiveness of four-quadrant gates and in-cab signaling to reduce grade crossing violations and collisions in Groton, Connecticut (*11*). In 2019 Ngamdung et al. evaluated the long-term effects of grade crossing violation photo enforcement, where video clips of violations were manually reviewed by Orlando, Florida city staffers to issue warnings (*12*). Baron et al. utilized video data to evaluate the effectiveness of in-pavement lights for grade crossing driver compliance (*13*). Jacobini and DaSilva utilized a camera system to evaluate the performance of gate skirts for preventing pedestrians from walking under the pedestrian gates of an active signalized crossing (*14*). These studies yielded important suggestions for how to design, improve, and evaluate grade crossing violation mitigation strategies. However, each of these studies was limited in duration due in part to the resources required to analyze more data.

Using AI and computer vision has the potential to overcome this resource limitation. This technology has been used to detect trespassers and grade crossing violations in railroad scenarios. As early as 2004, a study by Sheikh et al. at the University of Florida utilized computer vision to detect trespassers using a combination of techniques such as background subtraction, blob analysis, and region of interest (*15*). The combination of these techniques allows a computer to understand simple features and behaviors of moving objects. These same techniques were applied by Zhang et al. (*8*) and Zaman et al. (*9*) 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 (day versus night, clear versus inclement weather, etc.). AI algorithms have the potential to overcome these challenges, understand complex behaviors, and remain invariable to changing environmental conditions. Research by Zaman et al. in 2019 utilized Mask R-CNN (an image recognition AI algorithm) to detect trespassers at railroad grade crossings and rights-of-way (*7*).

The past decade has seen a rapid increase in the development of AI-driven computer vision algorithms. The development of deep convolutional neural networks (DCNNs) for image classification by Krizhevsky et al. (*16*) led to the development of a family of ever-improving object detectors: Regional CNN (*17*), Fast R-CNN (*18*), Faster R-CNN (*19*), and Mask R-CNN (*4*). 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 (*5*). Following its initial release, more efficient versions were developed: YOLO9000 (*20*), YOLOv3 (*21*), YOLOv4 (*22*), and YOLOv5 (*23*).

To fully detect and understand grade crossing violations, objects must be recognized and tracked. Although 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. In 2016 a tracking algorithm was published by Bewley et al. called Simple Online Realtime Tracking (SORT) (*24*). 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. added a deep association matrix to SORT (DeepSORT), allowing for objects to be tracked by deep neural features (*25*). Deep neural features include an object's 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.

YOLOv5 and DeepSORT were adapted in this project to recognize and understand grade crossing violations in real-time video of active grade crossings. These algorithms were selected for their superior accuracy and performance compared with 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. Terms used in the table are defined as follows.

- Frame per Second (FPS): the number of consecutive full-screen images that are displayed each second.
- Average Precision (AP): 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.

Methodology

The grade crossing violation system functions according to three discrete steps which are described in Figure 1. The system is initiated by the user providing a link to parse a live video stream. The system extracts the first frame and presents it to the user, where they then draw the region of interest (ROI) and identify the signal lights.

An ROI is a geometric shape within the video frame which indicates the area where violations 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 2. In Figure 2, the red box shows the limits of the ROI and the purple dots represent the region corresponding to the signal lights. Once completed, the algorithm will begin recognizing and tracking objects. The system has four modules: traffic, signal, grade crossing violation, and train.

Traffic Module

The traffic module recognizes objects using an adapted and custom-trained YOLOv5 algorithm. The objects are tracked using the DeepSORT algorithm (*24*). If an object crosses the ROI, it is logged as a traffic event. The classification (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. This information is collected to provide context for the risk of violation events. With this information, differences between the violator types and behaviors can be discerned.

Signal Module

The signal module recognizes the state of the grade crossing and determines whether it is active or inactive. This is accomplished through a computer vision algorithm that determines the relative brightness of the signal lamp and compares it with the brightness of previous frames. When this module indicates that the crossing is active, the grade crossing violation module becomes active. The signal activation algorithm only activates after 3 s of flashing are observed. This prevents false positives caused by illumination by headlights or other environmental factors. This delay also allows for drivers and pedestrians already within the crossing or just

Table 1. Summary of Relevant Computer Vision Algorithms

Paper	Objective	Dataset	Methodology	Result	Critique
DCNN (*16*)	Image classification	ImageNet	DCNN improves 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 (*17*)	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 as it performs CNN inference on many regional proposals. The selective search during the training process is also time-consuming.
Fast RCNN (*18*)	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 pretrained 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 (*19*)	Object detection	Pascal VOC MS COCO	A Region Proposal Network (PRN) 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 speed up as the training continues.
YOLO v1-v3 (*5*, *20*, *21*)	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 high-resolution classifier for faster inferencing.	66.4% of mAP in Pascal VOC. Faster than RCNN in inferencing.	YOLO has relatively low recall (more missed detections) compared with RCNN methods.
YOLOv4 (22)	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 (*24*)	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 mainly depends on fixed geometric features. Therefore, it is likely to lose track of objects after occlusion.
DeepSORT (*25*)	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.

Note: DCNN = deep convolutional neural networks; YOLO = You Only Look Once; DeepSORT = deep association matrix to SORT; SORT = Simple Online Realtime Tracking; RCNN = Regional Convolutional Neural Network; VOC = Visual Object Classes; COCO = Common Objects in Context; MS COCO = Microsoft Common Objects in Context; CNN = Convolutional Neural Network; RPN = Region Proposal Network.

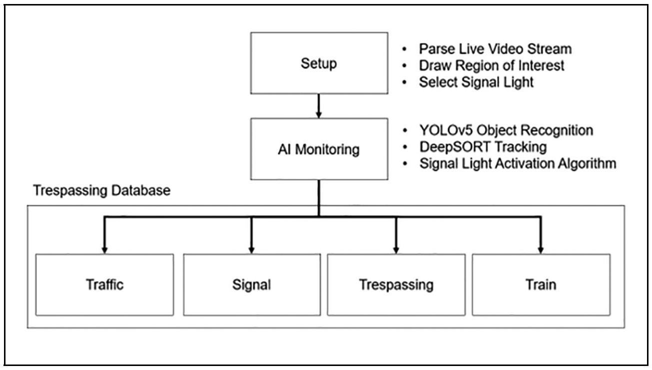

Figure 1. Grade crossing violation detection system framework.

Figure 2. Region of interest and signal light selection example.

perceiving the signals to clear the area before being counted as violators.

Grade Crossing Violation Module

Objects are recognized by the custom-trained YOLOv5 and are tracked using SORT. If the signals are active, violations 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 violation is recognized, the following information is collected: type (person, car, truck, bicycle, motorcycle), weather, start time, and duration.

Train Module

Finally, trains are recognized and detected by the system using a custom-trained YOLOv5 object class. These data are collected to help validate the system, and to understand how close a violator was to a train.

Case Study

The crossing in this study is in New Jersey and abuts a train station which is shared by multiple transit lines running on two tracks. Three parking lots servicing the station surround the crossing. Two of the parking lots are located to the west and one is located east of the crossing. The area is in a downtown commercial district with shopping centers, schools, and restaurants nearby. According to the latest U.S. Census estimates, the current population of the town where this crossing resides is approximately 15,000. According to an FRA report (*14*), three fatal pedestrian grade crossing accidents have occurred at the selected study site, in 2006, 2010, and 2016, respectively. Additionally, two vehicles that had stopped on the crossing were struck by transit trains in 2010 and 2012, respectively, with no noted injuries or fatalities. Table 2 shows a summary of grade crossing incidents at the studied crossing.

Grade Crossing Violation Data Collection

During this research, an internet protocol (IP) camera was installed on a utility pole located about 30 ft northwest of the grade crossing, facing southwest toward the grade crossing. In this case study, 272 days (6,582 h) of live video data were analyzed from January 1, 2021, to January 31, 2022. This video stream was continuously monitored by the AI for 24 h each day of the study period. However, the video stream was sporadically unavailable as a result of periodic maintenance and intermittent connection issues at the site. The video format is MP4 with a resolution of 704 $\times$ 576 pixels and a variable 5 to 15 frames per second. This AI analysis represents the longest continuous analysis of a grade crossing based on the reviewed literature.

The system correctly identified 20,054 violation events during the study period. A violation event represents an occurrence that may consist of multiple violators within a single record or video clip. In the stored 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 (*26*).

All records were manually reviewed and validated by the research team to ensure all violation events were correctly identified. There are two types of errors: false positives and false negatives. False positives are when the system reports a violation when none has occurred, and false negatives are when the system misses a violation.

Table 2. Summary of Crossing Incidents

Date of incident	Time	Type	Weather
6/9/2016	6:45 a.m.	Pedestrian fatal	Clear
9/15/2012	12:00 p.m.	Stalled empty vehicle struck, no injuries	Clear
8/4/2010	7:43 a.m.	Pedestrian fatal	Cloudy
5/21/2010	11:52 a.m.	Cement truck struck, no injuries	Clear
2/1/2006	6:48 p.m.	Pedestrian fatal	Clear

When these errors were detected in the development period, the algorithm was modified and retested to ensure system accuracy.

The system identified 29,252 total events, of which 20,054 (~69%) were true and 9,198 (~31%) were false positives. False positive rates were used to evaluate the system performance. A false positive rate is the ratio of false positives to total detections. False positive rates began as high as 30% in this research and declined to as low as 8% as the software was patched and the AI was retrained. There were four main causes of false positives discovered in the violation dataset: false activation detections, duplicate detections, legal occupiers, and misclassifications.

Approximately 80% 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. This challenge was ameliorated through the adoption of more sophisticated activation detection algorithms. Initial algorithms simply checked the illumination levels of the signal light but recorded false activations when vehicle headlights shone on the signal lights. The current algorithm has incorporated these conditions and checks for patterns in changing luminosity using a short-term Fourier Transform in addition to threshold parameters, resulting in greatly improved performance.

Approximately 10% of false positives were caused by duplicate detections. These were caused by a loss of tracking of the object because of low frame rates and occlusion. This was ameliorated through the adoption and tuning of the DeepSORT module. Approximately 5% 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 during the study period. These would occur intermittently. However, 90% of legal occupier false positives occurred on July 18th, 2022, during a single protracted maintenance event when police officers conducted traffic through the malfunctioning crossing. Approximately 5% 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 would manually review the raw video footage and identify all traffic, trespass, train, and signal events. The AI system would then analyze the same footage and report 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 violation 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 violations were missed by the system, resulting in a false negative rate of 0%. 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.

Results

In total, 20,054 grade crossing violation events were analyzed and visualized from several perspectives, showing weekly and hourly temporal heatmaps, violation rates by class, monthly and seasonal violation trends, a near-miss analysis, and violation trajectory analysis.

There were approximately eighteen pedestrian violations and sixty vehicle violations per day, which differs from past studies (*10*) conducted at this grade crossing. Past research by Zhang et al. showed a total of 158 pedestrian violations and seventy-four vehicle violations per day in 2018 and 2019. This study covered a year of grade crossing violations across four seasons, yielding a more comprehensive temporal and categorical analysis. Past research may have encountered weeks where violation rates were higher or lower than the true average. Additionally, past data were collected before COVID-19, which may have additional effects on pedestrian and vehicle traffic volumes.

(a)

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
	Hour of Day																								
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

(b)

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
	Hour of Day																								
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

(c)

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
	Hour of Day																								
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

(d)

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
	Hour of Day																								
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

(e)

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
	Hour of Day																								
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

(f)

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
	Hour of Day																								
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

Figure 3. Grade crossing violation heatmaps by time and day: (*a*) cars, (*b*) pedestrians, (*c*) trucks, (*d*) bicycles, (*e*) buses, and (*f*) total violations (January 1, 2021, to January 31, 2022).

Grade Crossing Violation Temporal Heatmap

Heatmaps of violation events for cars, pedestrians, trucks, bicycles, buses, and total violations across 1-h intervals for each day of the week are depicted in Figure 3. Approximately 11.2% of all violation events occurred between 7:00 and 8:00 p.m., which is the 1-h window with the highest percentage of violations. Car violations accounted for 69% and pedestrian violations for 23% of all violations. These findings are partially consistent with previous preliminary research conducted at this grade crossing (*10*), with the exception that past research showed higher counts of violations on weekends compared with weekdays.

Table 3. Factor Analysis of Grade Crossing Violations by Class (January 1, 2021, to January 31, 2022)

Class	Total traffic	Total grade crossing violations	Object class-based average daily traffic	Average grade crossing violations per day	Grade crossing violation 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

Figure 3 shows two temporal hot spots on weekdays from 5:00 to 8:00 p.m. and 6:00 to 8:00 a.m. These are consistent with typical commuter peak hours. Two main parking lots are located 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, returning commuters may need to traverse the crossing during the evening commute to reach the parking lots. This behavior may explain the relative severity of the afternoon violations compared with the morning peak hour. This observation holds true for both car and pedestrian violations. Peak hour car violations comprise 17% (morning) and 40% (evening) of all car violations. Peak hour pedestrian violations comprise 13% (morning) and 42% (evening) of all pedestrian violations.

This pattern is not shared by trucks, bicycles, or buses, which further reinforces the commuter violation hypothesis. For trucks, one assumption is that many truck drivers drive earlier in the day to avoid peak traffic on the road. Figure 3*c* shows a temporal hotspot during the 6:00–8:00 a.m. interval.

During the study period, 6,962 violations occurred during the commute hours from 5:00 to 8:00 p.m. This represents approximately 35% of all violations occurring during only 17% of the hours of the week. Identifying the evening commute temporal hotspot can aid in the efficient deployment of transit police to ameliorate violations during this time slot. Vehicle violations could be further reduced with the implementation of a photo enforcement system and targeted high-visibility traffic signs (*27*).

Grade Crossing Violation Rates by Class

Table 3 shows the factor analysis of five different types of grade crossing violators. During the study period, the total car, pedestrian, truck, bicycle, and bus traffic data were collected, and the average daily traffic was calculated by class.

In Table 3, 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 violation rate among all classes, which indicates that this class is the least compliant and may be targeted for mitigation strategies. Buses are the most compliant class and have the lowest violation rate of all classes. This may be because of the specific training that bus drivers receive to stop and proceed at all grade crossings.

Grade Crossing Violation Rates by Class Normalized by Traffic

Figure 4 shows weekly and hourly temporal heatmaps of the grade crossing violation rate per thousand for cars, pedestrians, trucks, bicycles, buses, and total violations across 1-h intervals for each day of the week. The grade crossing violation rate per thousand is obtained by dividing the number of grade crossing violations in each timeslot by the number of corresponding traffic and multiplying by 1,000. This rate per thousand is selected to emphasize and clarify the values in context.

Figure 3 shows that more grade crossing violations occurred during evening peak hours. However, when normalized against traffic, grade crossing users are shown to be less compliant during the morning peak hours from 6:00 to 8:00 a.m. Figure 4 indicates that even though more trespassing occurs during the afternoon commute, all classes are less compliant in the morning hours. This insight may help to focus enforcement solutions on effectively mitigating trespassing during the least compliant hours. Additionally, a difference in grade crossing violation rate per thousand can be seen between weekdays and weekends. This finding could lead to more effective time-targeted law enforcement efforts.

Grade Crossing Violation Rates by Class Normalized by Signal Activations

Figure 5 shows a temporal heatmap of the total number of signals for each hour of the day and day of the week for the study period. There were a total of 20,020 signal

(a)

	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

(b)

	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

(c)

	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

(d)

	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

(e)

	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

(f)

	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

Figure 4. Grade crossing violation rate per thousand heatmaps by time and day: (*a*) cars, (*b*) pedestrians, (*c*) trucks, (*d*) bicycles, (*e*) buses, and (*f*) total violations (January 1, 2021, to January 31, 2022).

	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 5. Total grade crossing activations (January 1, 2021, to January 31, 2022).

activations during the study period and 4,957 (25%) of them occurred on weekdays between 5:00 and 8:00 p.m.

Figure 6 shows weekly and hourly temporal heatmaps of the grade crossing violation rate per signal activation for cars, pedestrians, trucks, bicycles, buses, and total violations across 1-h intervals for each day of the week. The grade crossing violation rate per signal activation is obtained by dividing the number of grade crossing violations by the number of signal activations in each 1-h interval.

Total violations per signal activation share a similar temporal intensity pattern as total violations but differ when compared with trespassing rates per thousand

(a)

	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

(b)

	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

(c)

	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

(d)

	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

(e)

	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

(f)

	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

Figure 6. Grade crossing violations per signal light heatmaps by time and day: (*a*) cars, (*b*) pedestrians, (*c*) trucks, (*d*) bicycles, (*e*) buses, and (*f*) total violations (January 1, 2021, to January 31, 2022).

pedestrian and vehicle traffic passes. The graphic shows higher violation rates per signal during the morning weekday peak hours of 6:00–8:00 a.m. and evening peak hours of 5:00–8:00 p.m. These hours also have a high number of signal activations, which increases the opportunities for grade crossing violations to occur.

Car violations per signal activation show a change in temporal intensity compared with the total car violation rates and car violation rate per thousand heatmaps. Car violation rates per signal activation are highest on Mondays at 7:00 a.m. and all days of the week between 5:00 and 8:00 p.m. Despite fewer grade crossing activations occurring on weekends, the violation rate per signal activation is high every day of the week. The highest car violation rate per signal activation is on Monday mornings at 7:00 a.m. Pedestrian violations per signal

Table 4. Grade Crossing Violations by Month (January 1, 2021, to January 31, 2022)

Month	Car	Pedestrian	Truck	Bicycle	Bus	Total	Ratio of total violations	Ratio of total traffic
Jan 2021	1,416	282	98	14	0	1,810	6.61%	7.61%
Feb 2021	906	176	106	6	0	1,194	4.36%	4.75%
Mar 2021	1,375	313	123	14	1	1,826	6.67%	9.21%
Apr 2021	1,339	351	203	19	0	1,912	6.99%	9.49%
May 2021	1,084	291	149	28	2	1,554	5.68%	9.89%
Jun 2021	2,019	671	352	65	0	3,107	11.35%	9.97%
Jul 2021	1,786	817	306	42	0	2,951	10.78%	9.73%
Aug 2021	1,519	870	198	47	1	2,635	9.63%	8.59%
Sept 2021	1,363	696	154	31	0	2,244	8.20%	8.59%
Oct 2021	1,856*	572*	196*	19*	3*	2,646*	9.67%	8.83%
Nov 2021	1,765*	424*	148*	7*	3*	2,347*	8.58%	5.99%
Dec 2021	1,761*	409*	133*	11*	3*	2,317*	8.47%	5.52%
Jan 2022	623	144	53	1	0	821	3.00%	1.80%
Total	18,812*	6,016*	2,219*	304*	13*	27,364*	100%	100%

Note: Data were limited between October 2021 and December 2021 because of intermittent stream unavailability and video corruption, which prevented full manual validation. Data affected by this issue are denoted with an asterisk. Additionally, data from January 2022 were partial and only include ten full days of analysis.

activation show a change in temporal intensity compared with total pedestrian violations and pedestrian violation rates per thousand. The highest pedestrian violation rates per signal activation are on Wednesdays at 6:00 p.m. and Sundays at 11:00 a.m. The presence of emergent 1-h hotspots provides an opportunity for targeted enforcement to address the hours with worst compliance.

Truck violations per signal activation show a similar trend in temporal intensity compared with total truck violations and truck violation rates per thousand. In each of the heatmaps, the hours of 6:00–8:00 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 these hours could be maximally effective.

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

Grade Crossing Violations by Month of Year

Detailed information for grade crossing violations by month is shown in Table 4. This table includes the total violations by each class for each month. Additionally, the proportion of all observed violations and traffic is shown by month. Figure 7 further illustrates the breakdown of the grade crossing violations by month for the various types of violators. Data were limited between October 2021 and December 2021 because of intermittent stream unavailability and video corruption, which prevented full manual validation. Data affected by this issue are denoted with an asterisk. Additionally, data from January 2022 were partial and only include ten full days of analysis.

From January 2021 through May 2021 and in September 2021 the proportion of violations was less than the proportion of total traffic. This indicates better compliance at the crossing during these months as compared with August 2021 and from October 2021 through January 2022.

Car violations occurred most frequently in June 2021 (15% of all car violations). The peak months for pedestrian, truck, bicycle, and bus violations were June, July, and August of 2021. This shows a seasonal trend. A positive reduction in grade crossing violations could be expected through target-specific education and by increasing law enforcement during peak months (*28*, *29*). Operation Lifesaver blitzes could be planned during these months to efficiently target months with the worst trespassing rates.

Grade Crossing Violations by Season

In Figure 7, the peak months of grade crossing violations indicate the potential relationship between seasons and violations. The spring months are April, May, and June. The summer months are July, August, and September. The fall months are October, November, and December. The winter months are January, February, and March. Figure 8*a* shows the grade crossing violation rate per

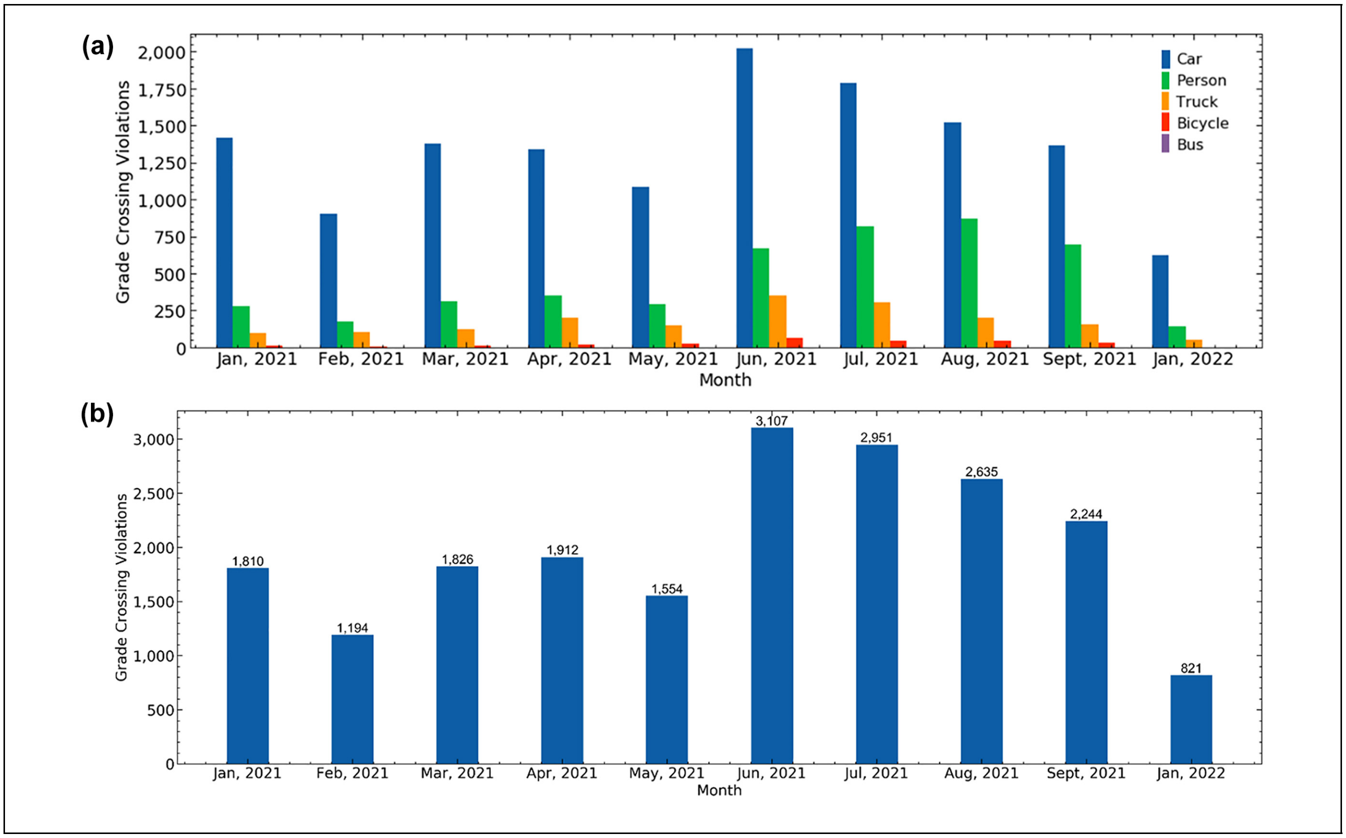

Figure 7. Grade crossing violations by month: (*a*) by class and (*b*) total violations (January 1, 2021, to January 31, 2022).

thousand by season and Figure 8*b* shows the violation rate per thousand by class and season. These values were obtained by dividing the number of violations by the volume of traffic during the corresponding season and multiplying by 1,000. This normalization helps address the data inconsistencies from October to December 2021.

The highest violation rate occurred during the summer, followed by winter, fall, and spring, accordingly. Most of the violations occurred in summer (43.3% of the total violations), which is consistent with the findings of previous research (*10*) conducted at this grade crossing. In Figure 8*b*, the class-specific grade crossing violation rate per thousand for each season is shown. These values were obtained by dividing the number of grade crossing violations in each season by the amount of corresponding traffic and multiplying by 1,000.

The data show that pedestrian violation rates are higher in summer and fall than in winter and spring. Car violation rates have a smaller fluctuation by season with nearly identical rates during summer and winter, and with slightly lower rates in fall and spring. Truck violations have the highest values in summer and are lower in winter, spring, and fall. Bicycle violations have similar rates in summer and winter, and lower rates in spring and fall. The few bus violations that were observed occurred in spring and summer. For most classes, summer had higher violation rates. Specially timed and target-specific education and law enforcement blitzes could focus on the summer season to achieve improvement in grade crossing safety.

Grade Crossing Violation Near-Miss Analysis

In this research a near-miss grade crossing violation is defined as a violation that occurs after the signals have activated but before the train has arrived, indicating a potential collision with the train. Some 4,295 trespassing events occurred before the train arrived, comprising 21% of the total dataset. The near-miss time was obtained by subtracting the nearest time of train arrival from the time of grade crossing violations 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 9. The large number of events with no trains detected can be explained by the crossing's proximity to a transit 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

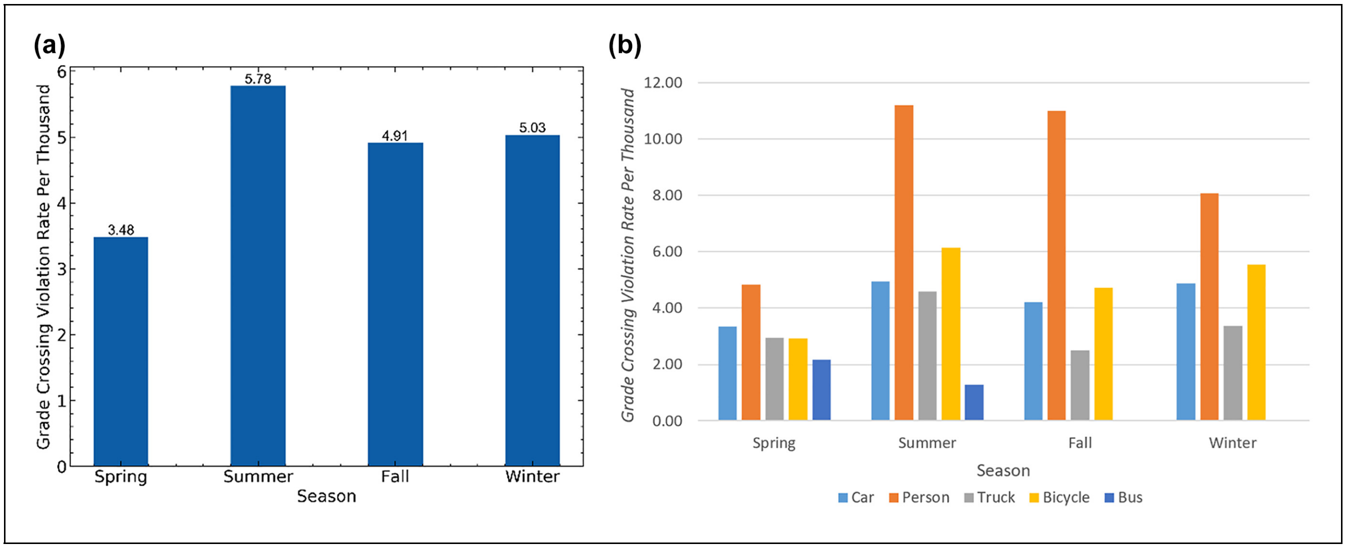

Figure 8. (*a*) Grade crossing violation rate per thousand by season and (*b*) grade crossing violation rate per thousand by class and season (January 1, 2021, to January 31, 2022).

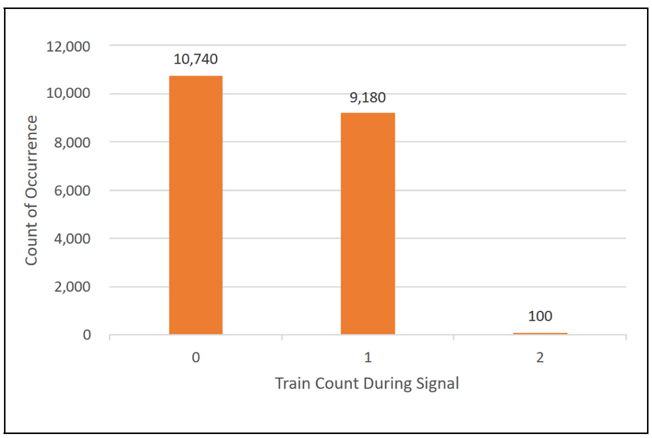

Figure 9. Train counts during signals from January 1, 2021, to January 31, 2022.

begins to depart the station, the signals will reactivate and the train will be detected traversing the crossing.

The near-miss analyses of the violation events for cars, pedestrians, trucks, bicycles, buses, and total violations are shown in Figure 10. In this figure, each dot represents the total number of violations 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 s. In Figure 10, 45 s between the train and violation was chosen as the cutoff to illustrate the different patterns between classes.

The near-miss distribution for all types of grade crossing violations indicates an average near-miss time of 30.8 s. Some 81% of grade crossing violations occurred within 20–40 s of near-miss time. About 1% of grade crossing violations occurred within less than 10 s of near-miss time, which represents an extremely dangerous scenario.

In the distribution for car violations, two peaks were observed, centered around 20 s and 35 s. The crossing is adjacent to a nearby station, and the crossing 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 alighted from the train, the train will proceed and the crossing will activate again. Violations by individuals during the first activation are likely to have occurred approximately 35 s before the train arrives, whereas violations during the second of these activations are centered around the 20 s peak.

For the grade crossing car and truck near-miss distribution, most violations occurred within 20–40 s, and the average near-miss time is about 30 s, whereas the average near-miss times for pedestrians and bicycles are 33 s and 36.2 s, respectively. The speed difference between motor vehicles and pedestrians/bicycles may cause this average difference of near-miss times, but this conclusion requires more evidence.

Grade crossing violation examples that occurred within less than 10 s of a train's arrival can be seen in Figure 11. In Figure 11*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 11*b*, the pedestrian entered the grade crossing when the gate was fully horizontal and the train entered the ROI within 10 s. Both situations are extremely dangerous for the violators and should be given the utmost attention when developing mitigation strategies.

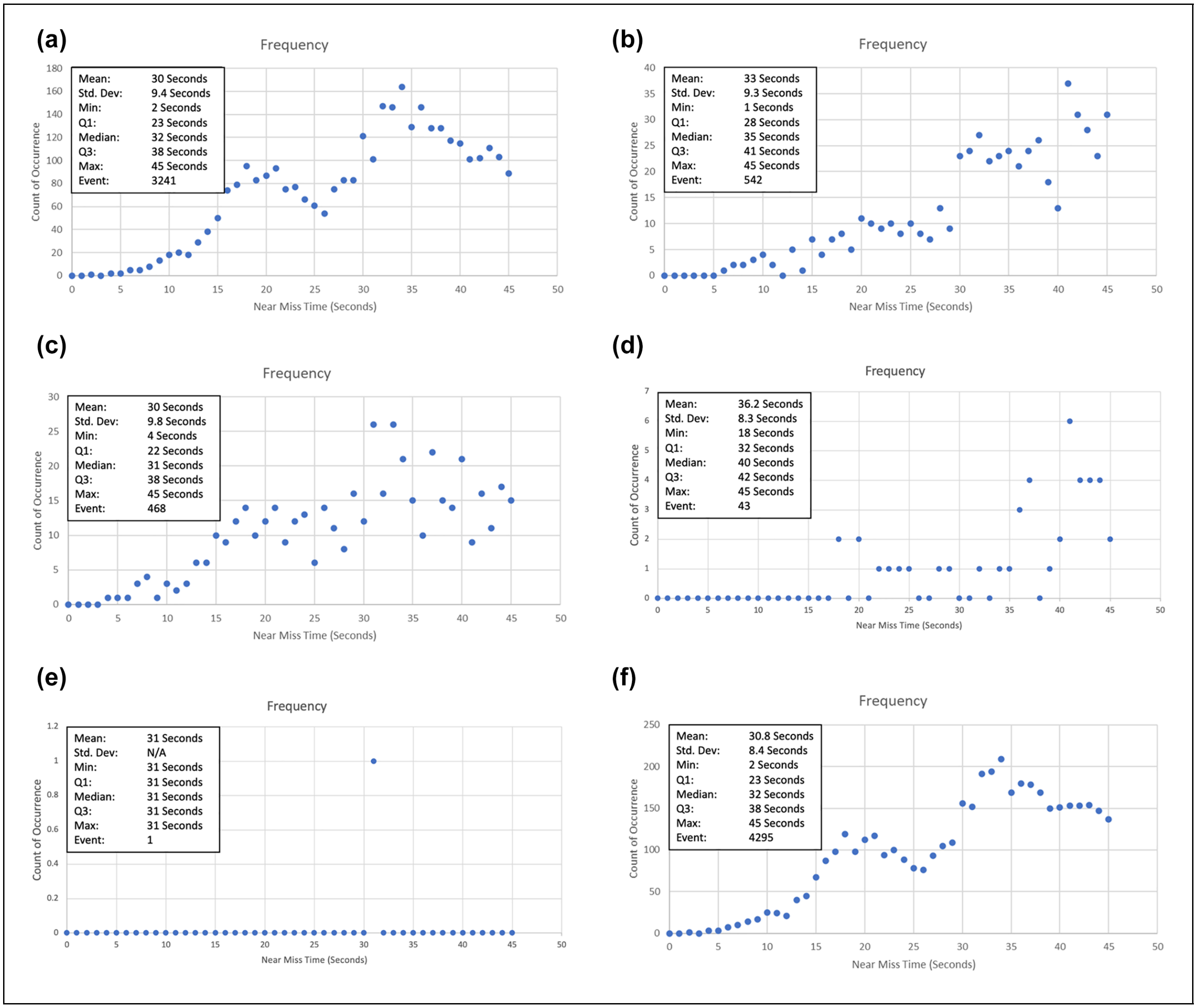

Figure 10. Near-miss distribution of grade crossing violations: (*a*) cars, (*b*) pedestrian, (*c*) truck, (*d*) bicycle, (*e*) bus, and (*f*) all violations (January 1, 2021, to January 31, 2022).

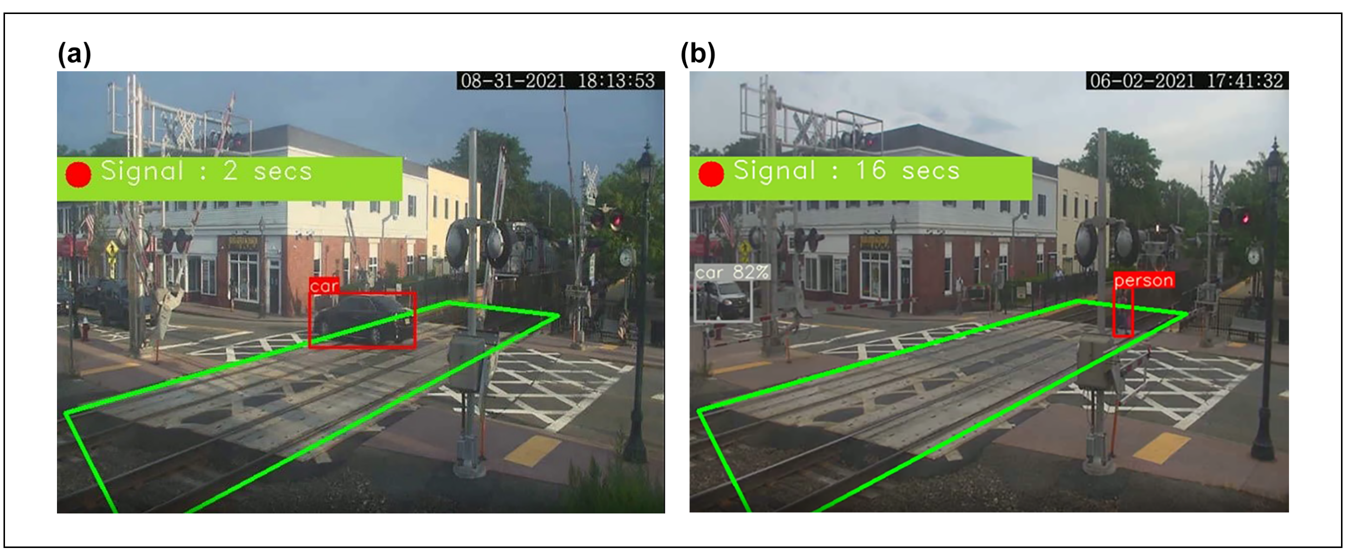

Figure 11. (*a*) Grade crossing car violation and (*b*) grade crossing pedestrian violation that occurred within 10 s of a train's arrival.

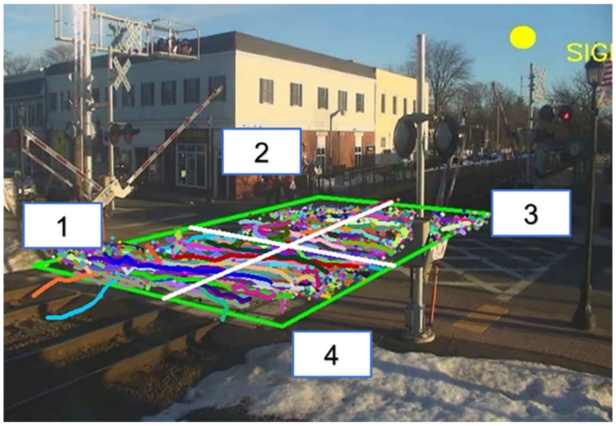

Figure 12. Trajectory of grade crossing violation.

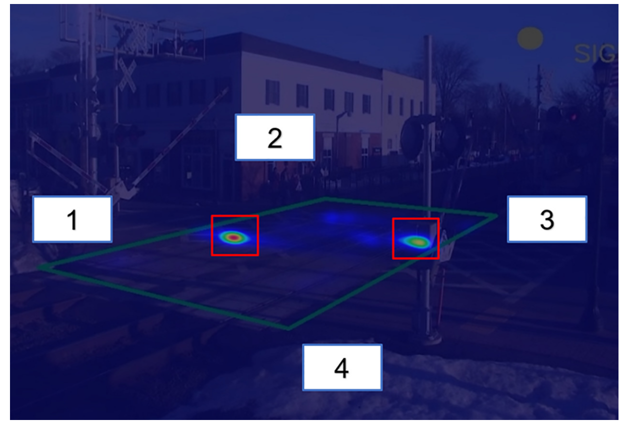

Figure 13. Heatmap of normal-view grade crossing violation.

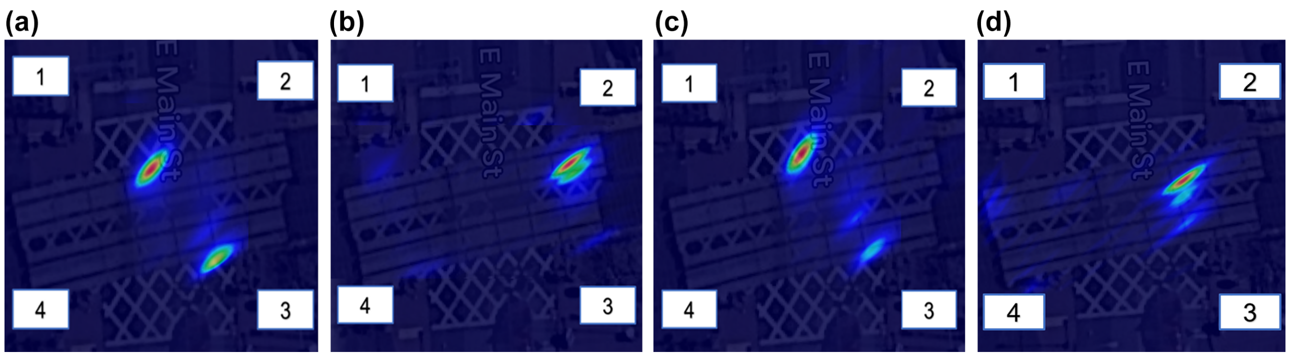

Figure 14. Heatmap of aerial-view grade crossing violation: (*a*) cars, (*b*) pedestrians, (*c*) trucks, and (*d*) bicycles.

Grade Crossing Violation Trajectory Analysis

This research captured trajectory information of grade crossing violations using the DeepSORT module. The DeepSORT module records the path of each grade crossing violation. In Figure 12, a total of 20,054 trajectories are visualized into four zones. This trajectory information reveals the flow of violators and leads to suggested potential actions to decrease violations. Furthermore, heatmaps were generated for all violations in the camera's field of view (Figure 13) and from a transformed aerial view (Figure 14).

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 grade crossing violation. In relation to the normal-view violation heatmap, two hotspots are identified in zone 1 and 3, which provide more evidence to inform potential grade crossing violation mitigation decisions.

Car and truck violations originated in zone 1 and ended in zone 4 more often than they originated in zone 3 and ended in zone 2. One resulting hypothesis is that the traffic flow could be heavier on the zone-1-to-4 side, resulting in more frequent violations. Trajectory information was not recorded for traffic data, so we 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 violations. More evidence is needed to validate either hypothesis.

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

Table 5. Grade Crossing Violations by Zone Origin and Destination

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

Note: NA or Not Applicable represents origin destination pairs where the origin is the same as the destination. These pairs were not included in this analysis.

Table 5 shows the origin and destination analysis of four zones of grade crossing violation for 10,334 (52%) of the violations. A limited set of trajectories was selected because of incomplete trajectory arrays for some of the violations. 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 near lane. When combining all violations, 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% of the total number of violations (8,792 out of 10,334 violations).

Data-Driven Violation Mitigation Recommendations

In this case study, grade crossing violation distributions and relative behaviors were analyzed and provide evidence for potential actions to decrease grade crossing violations. This research shows the potential feasibility of deploying this system at other locations to gather violation data and inform mitigation activities. As the deployment of this technology increases, a corresponding decrease in the amount of effort needed to achieve acceptable performance is expected. This decrease will lead to faster adoption of this technology throughout the railroad industry. The customization of the algorithm for this effort requires sample data gathering, manual annotation, AI analysis, and refinement. The largest and most laborious task in this process is manual annotation, which is required to ascertain the AI's performance by comparing it with ground truth.

As the AI encounters each new location, the research team improves the AI in two major ways: (1) new signal activation algorithms are created, and (2) new images are annotated to retrain the AI. With each new grade crossing there is the possibility of encountering a new signal type based on the field of view. Determination of the signal status is required to identify violations. In this research only flashing signals were encountered and therefore only a single activation algorithm was required. Traffic signals, signal bars, crossing gate arms, and other types of flashing lights could be encountered at new locations. Therefore, the development of two new algorithms and testing to ensure accuracy under varying conditions will be required.

This process outlines one required customization effort which will reduce over time as more activation algorithms are developed. Eventually, an algorithm for most signal types will be developed and a methodology for minimizing the customization time will be put into practice.

Secondly, with a new field of view, lighting conditions, and angle, the ability of the system to accurately detect people, vehicles, and other objects may decrease. For example, in a new field of view, people may look slightly different than those in the images used to train the AI. Specifically, if images of people from a horizontal field of view were used to train the AI and the system was installed with a top-down view it would have difficulty identifying pedestrians. If this difference is large enough, new images will need to be annotated and incorporated into the AI's training to accurately detect classes of interest.

Generally, about seventy-nine grade crossing violations occur each day in this location. The findings of this research are coherent with previous research (*10*) and could provide more guidance for law enforcement, education, and engineering. Based on the analysis of this case study, three grade crossing violation reduction strategies are proposed. The effectiveness of all recommended strategies could be evaluated by collecting violation data with the algorithm developed in this study.

Introducing More Police Officers at the Peak Grade Crossing Violation Hours

According to the grade crossing violations distribution, about 35% of violations occur from 5:00 to 8:00 p.m. on weekdays, which corresponds to the commuter schedule. Most grade crossing violations occur from 7:00 to 8:00 p.m. on Friday. However, when normalized by traffic, all classes are least compliant during morning weekday peak hours. The FRA (*28*) identifies law enforcement strategies for reducing grade crossing violations, which include increasing enforcement patrols at targeted violation hotspots. Thus, police patrols could be introduced during these temporal hotspots to prevent grade crossing violations and to guide traffic.

Additionally, most grade crossing violations occur in the summer, and more police officers could be deployed during the summer season to decrease potentially unsafe grade crossing events. Overall, this strategy could prevent approximately 7,000 (35%) unsafe grade crossing events per year. Further studies should be conducted to understand the effectiveness of enforcing compliance during hours with peak violations, or during hours with the least compliance normalized by traffic volumes.

Targeted Education Blitzes During the Summer

To reduce potential grade crossing violations, safety education should focus on communities surrounding railroads and grade crossings. Moreover, the highest rate of grade crossing violations by cars was in June and the highest rate of violations by pedestrians was in July. Therefore, more education about the legal and safety consequences of grade crossing violations could be provided during the summer to reduce the likelihood of violations. Four bus violations were detected at this grade crossing. Even though this was the smallest of the detected classes, they represent a high-risk scenario should an incident occur. Bus driver education should be reinforced to further reduce violations. Education materials like posters and warning signs could also be provided near the grade crossing to promote public education and reduce grade crossing violations. Generally, deployment of this strategy would mean that about 8,700 (43%) grade crossing violators per year could be influenced, decreasing potential violations.

Engineering with Barriers and Photo Enforcement System of the Grade Crossing

Researchers from the U.S. Department of Transportation (*30*) conducted an analysis of 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 violations. In that case study, vehicles, pedestrians, and bicycles accounted for 76%, 23%, and 1% of the total violations, respectively. Photo enforcement systems at a grade crossing have been shown to reduce violation rates by 17% in past research by Ngamdung et al. (*12*) and Ngamdung and DaSilva (*27*). Similar grade crossing violation reduction could be expected at this location if such engineering actions were adopted. In summary, additional gate skirts, road barriers, and a photo enforcement system could mitigate unsafe grade crossing violations by vehicles, pedestrians, and bicycles.

Conclusion

The goal of this paper was to develop and utilize an AI system to automate grade crossing violation data collection. This study analyzed approximately 1 year of live video footage, 24 h per day, at a grade crossing in New Jersey. The system detected 20,054 grade crossing violation events at the selected grade crossing. The system can also detect and classify by type, weather information, and train events for further data analysis. The system suffered from some false positives during the study period, which were discovered, ameliorated, and omitted from the results. The grade crossing violation data were analyzed and visualized by hour of day, day of week, and temporal heatmaps, and breakdowns by classification were shown. Recommendations were proposed based on information provided by the AI system. Further research could increase the amount and variety of data analyzed by the AI system, providing a better understanding of grade crossing violation behavior and more informed mitigation strategies.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Xiang Liu, Asim Zaman; data collection: Zhe Huang, Huixiong Qin; analysis and interpretation of results: Weitian Li; draft manuscript preparation: Di Kang. All authors reviewed the results and approved the final version of the manuscript.

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Data Accessibility Statement

Raw video data and grade crossing violation records are not available because of data sharing restrictions established by a non-disclosure agreement with the collaborator.

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