RAILROAD TRESPASSING DETECTION AND ANALYSIS USING VIDEO ANALYTICS

By

ASIM FRANCIS ZAMAN

A thesis submitted to the

School of Graduate Studies

Rutgers, The State University of New Jersey

In partial fulfillment of the requirements

For the degree of

Master of Science

Graduate Program in Civil and Environmental Engineering

Written under direction of

Dr. Xiang Liu

And Approved by

____

____

____

New Brunswick, New Jersey

October 2018

ABSTRACT OF THE THESIS

Railroad Trespassing Detection and Analysis using Video Analytics

By ASIM FRANCIS ZAMAN

Thesis Director:

Dr. Xiang Liu

Trespassing is the leading cause of rail-related deaths and has been on the rise for the past ten years. Detection of trespassing of railroad tracks is critical to understand and prevent trespassing fatalities. The volume of video data in the railroad industry has increased significantly in recent years. Surveillance cameras are situated on nearly every part of the railroad system such as inside the cab, along the track, at grade crossings, and in stations. These camera systems are manually monitored; either live or subsequently reviewed in an archive, which requires an immense amount of labor. To make the video analysis much less labor-intensive, this thesis develops two frameworks for utilizing Artificial Intelligence (AI) technologies for the extraction of useful information from these big video datasets.

The first framework has been implemented on video data from one grade crossing in New Jersey. The AI algorithm can automatically detect unsafe trespassing of railroad tracks. To date, the AI algorithm has analyzed hours of video data and correctly detected all trespassing events. The algorithm was presented to industry professionals and useful feedback was gathered suggesting several improvements to meet the needs of the railroad industry. This feedback led to the development of the second framework with new capabilities, and an expanded scope of video data reviewed.

The second framework was implemented on three railroad video live streams, a grade crossing and two non-grade crossings, in the United States. This AI algorithm automatically detects trespassing events, differentiates between the type of violator (car, motorcycle, truck, pedestrian etc.) and sends an alert text message to a designated destination with important information including a video clip of the trespassing event. In this study, the AI has analyzed hours of live footage with no false positives or missed detections.

This thesis indicates the promise of using AI for automated analysis of railroad big video data, thereby supporting data-driven railroad safety research. This thesis, and its sequent studies, aim to provide the railroad industry with next-generation big data analysis methods and tools for quickly and reliably processing large volumes of video data to better understand human factors in railroad safety research.

Acknowledgements

This thesis was achieved with the support and help of many individuals.

I thank my advisor, Dr. Liu for his continual support and leadership. This thesis would not have been possible without his help. His backing for this research and career development has been instrumental in me getting to where I am today. I am forever grateful for his patience and guidance.

I extend my thanks to the members of my thesis committee Dr. Jie Gong and Dr. Jing Jin, whose cooperation, feedback and suggestions have played an integral role in the completion of this research.

I also wish to thank Chintan Trivedi, Zhipeng Zhang, Kshitij Shah, Baozhang Ren and the other students from Rutgers for their support, inspiration and friendship.

To my family, thank you for always being my biggest teachers and supporters. Throughout my life you have shown me how hard work, determination and compassion allows one to achieve anything.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Trespassing in the Railroad Industry

"Trespassing on railroad property is the leading cause of all rail-related deaths." (1) This statement made by Ronald L. Batory, the Administrator of the Federal Railroad Administration (FRA), at the 2018 American Public Transportation Association Rail Conference encapsulates the biggest problem in railroad safety today. Trespassing deaths account for a large portion of all railroad fatalities and since 2012 the number of total trespassing casualties has increased significantly. (2,3) This trend has led to a ten-year high in 2017 where 575 of the total 888 fatalities were trespassers. (4) This issue is recognized as a major concern of safety within the US, which is supported by the U.S. House Committee on Appropriations Fiscal Year 2018 Transportation Budget Report which instructs the FRA to "to identify and study the causal factors that lead to trespassing incidents on railroad property and develop a national strategy to prevent trespasser accidents" (5).

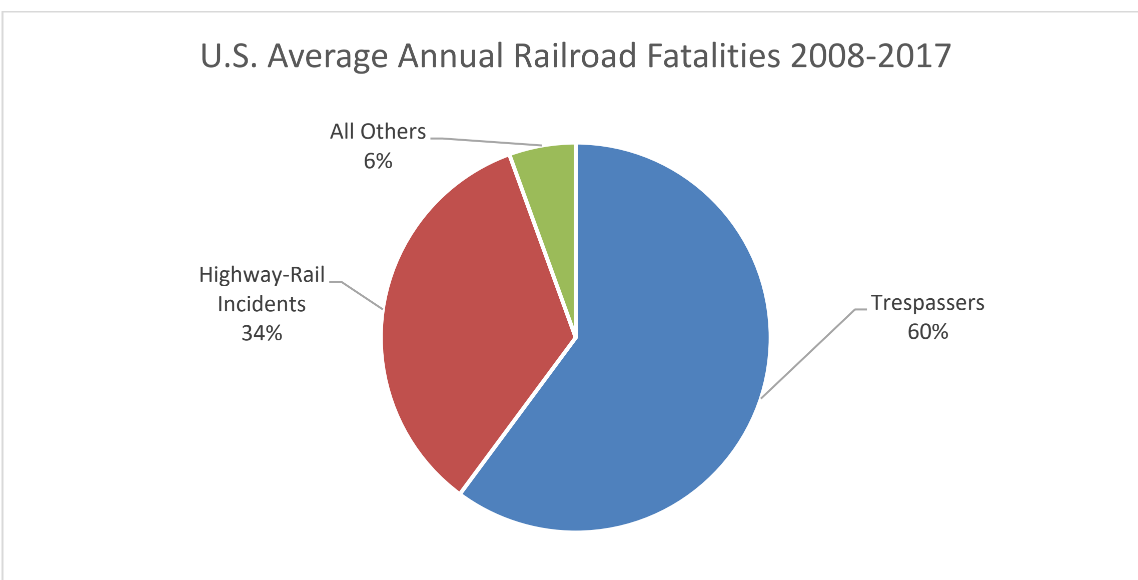


Figure 1 U.S Average Annual Railroad Fatalities 2008-2017 (6)

Many trespassing events occur within the railroad industry that do not result in injuries or fatalities. Because no actual harm occurs, these trespass events are typically not recorded in FRA safety databases. In majority, trespassing events manifest themselves in two scenarios in the railroad industry, at highway rail grade crossings and on railroad rights-of-way. At active signalized highway rail grade-crossings, if a pedestrian or vehicles crosses while the barrier gates and flashing lights are deployed it is classified as a trespassing event. Additionally, if a pedestrian or vehicle enters a railroad right-of-way without authorization it is also classified as a trespassing event. Although these events do not cause actual damage, they indicate certain characteristics, which may ultimately result in severe consequences if they occur repeatedly. Learning from trespassing data is an important research topic in proactive risk management and is critical for developing effective education, enforcement and engineering strategies for the prevention of trespassing on railroad tracks. (7)(8)

1.2 Railroad Video Data

The availability of video data in the railroad industry is increasing every year and enables the acquisition of data on trespassing. Cameras are sited on nearly every part of the railroad system, such as inside the cab, along the track, at grade crossings, and in stations. The Fixing America's Surface Transportation (FAST) Act requires all passenger railroads to install inward-facing cameras to better monitor train crews and assist in accident investigations, and outward-facing cameras to better monitor track conditions (9). The Los Angeles Metro Transit Authority in California began utilizing video cameras for law enforcement at grade crossings (9). In the New York area, Metro-North and the Long

Island Rail Road received $5 million from the FRA for grade crossing improvements. Approximately 40% of those funds were committed to installing a Closed-circuit Television (CCTV) system on high-risk grade crossings (10).

The increase in availability of video data within the rail industry makes acquiring data on trespassing more viable. Caltrain in Palo Alto California has installed CCTV cameras at safety critical grade crossings for this exact purpose, to actively monitor and prevent illegal crossings through an integrated alert system. (11) This trend has also expanded globally as India has an initiative to install cameras on over 11,000 trains and 8,500 stations for safety purposes throughout the country starting in 2018. (12) These sources provide valuable video big data sources for railroads but analyzing the data accurately in real-time is challenging.

The pervasive presence of surveillance cameras provides a big data platform for collecting and analyzing trespassing data in support of railroad safety and risk management. Despite its value, video data analysis can be extremely laborious, usually taking hours or days to process and analyze. At present, most camera systems are reviewed manually by railroad staff, but limited resources and operator fatigue (13,14) can lead to potentially missing trespassing events.

1.2.1 Video Data for Railroad Safety Research

In the railroad industry, the extraction of useful information from video data has largely been based on manual reviewing of the gathered footage. For example, Ngamdung et al. (15) conducted a study to understand illegal trespassing of railroad property in Pittsford, New York. The video analysis was conducted manually and required a large amount of labor to accomplish (16). In addition, there have been studies on the effectiveness of humans watching CCTV cameras; they show that after 20-40 minutes of active monitoring, operators often suffer from "video-blindness," which reduces their ability to effectively complete their task (13).

Minimal work has been done to utilize AI for trespassing and no studies have performed these analyses in real time, providing alerts for proactive trespass prevention, which is a principle knowledge gap motivating this study. Research by Pu et al in 2014 used a series of computer vision algorithms to detect illegal crossings with a facsimile of a grade crossing. (17) Further research by Zhang et al and Zaman et al (18,19) used a similar suite of AI algorithms to detect trespasses at grade crossings. These studies were limited to the available archival footage and did not analyze real-time video feeds. The live detection of more trespassing events at both grade crossings and non-grade crossings can support railroads in two ways. The first is the potential for faster responses dangerous situations on their property. Secondly, the aggregated database of these events can give insight into the behavioral characteristics of trespassers.

Effort has been made to quantify the frequency and severity of highway-rail grade crossing incidents. Previous studies (20,21) employed the U.S. Department of Transportation (USDOT) Accident Prediction Model to estimate the number of collisions occurring at grade crossings. An understanding of driver behavior and human factors can contribute to grade crossing safety improvement (22). A comprehensive overview of grade crossing research is summarized in Chadwick et al. (23). Since grade crossing incidents account for a large portion of casualties on U.S. railroads (3,23), it is important to better understand this type of risk so as to develop proper risk mitigation strategies.

1.3 AI Technologies for Video Analytics

Artificial Intelligence has the potential to reduce the required labor to detect trespassers in railroad video data. Evidence of this is demonstrated by the utilization of AI algorithms in parallel industries such as highway and aviation.

1.3.1 Computer Vision for Video Analytics

Selected AI techniques include background subtraction, region of interest, and Kalman filtering (24–27). The first and most fundamental tool in video analytics is background subtraction. When attempting to isolate moving objects in a frame, the removal of the landscape against which they are moving can improve processing time and accuracy. Originally, cameras at airports were used to provide visual confirmation of a plane's identity, and infrared cameras were used to ensure security from trespassers. In recent years, a network called the Autoscope Solo Wide Area Video Vehicle Detection System has been deployed in European airports. This system utilizes background subtraction in its AI to identify moving objects within the field of view (24). Other techniques of big video analysis, region of interest (ROI) and line of interest (LOI), were implemented in a study counting pedestrians and cyclists crossing an intersection using a stationary CCTV camera. A user can define a line or polygon of pixels in the frame which an AI can use as a reference. In that study, pedestrians and cyclists were tracked in the frame and only counted as “crossing” if they passed through the ROI (27). Another AI technique is the Kalman filter, which is a set of mathematical equations to estimate the state of a process (25). This technique has been used to track vehicles within a camera view for highway applications (26).

While AI has the potential to provide useful data analysis capabilities, there are privacy concerns which may occur due to collecting personally identifiable information (28,29). For example, a survey showed that 88% of Americans “do not wish to have someone watch or listen to them without their permission” (30). 63% of respondents “feel it is important to be able to go around in public without always being identified” (30). This opinion has fueled legal and technological changes to preserve the privacy of individuals. For example, in 1974 the United States congress enacted the Federal Privacy act, which regulated governmental databases in how they could store and publish information on its citizens (31). Therefore, it is important to recognize and manage these privacy concerns. In 2009 the Federal Trade Commission (FTC) published a general set of principles for the collection of information, including awareness, consent, access, security and enforcement (32). To maintain these principles and still extract useful information, specialized video processing techniques have been developed to preserve privacy. Google’s Street View’s anonymization techniques are among the examples of how these concerns are technologically considered. The anonymization techniques involved an intricate neural network approach that first identifies faces and then performs a post processing obfuscation resulting in a final anonymized image (33). In a full-scale implantation of video analysis frameworks, a similar anonymization algorithm could be implemented to preserve privacy.

1.3.2 Mask R-CNN for Trespass Detection

An emerging type of AI algorithm called Mask R-CNN has been successfully used in analyzing big video data in similar circumstances to the railroads trespassing problem. Mask R-CNN is built on the established architecture of deep convolutional neural networks (DCNN). DCNNs are a style of neural network that classifies images through a specific arrangement of three kinds of network layers; convolutional, rectified linear units and pooling layers. The Convolutional layers, for which this algorithm is named, attempt to find a pre-programmed feature (called a filter) within an image. This can be a geometric shape, series of colors or any other element that is unique to what is intended to be classified. Multiple filters are tested across the entire image and are aggregated into a single image in the pooling layer. Rectified unit layers (ReLU) remove anything that doesn't match resulting in an image only showing what may match. If these steps are repeated in the algorithm, convolving, pooling and convolving again, your algorithm becomes deep, resulting in a deep convolutional neural network.(34)

Since Krizhevsky et al's (35) 2012 research publication using DCNNs for image classification, which was used to win the ImageNet LSVRC-2012 contest (correctly classifying 1.2 million images), the use of DCNNs in image classification has rapidly increased in popularity. Subsequent research based on Krizhevsky' s work e.g. (Regional CNN (36), Fast R-CNN (37) and Faster R-CNN (38)) built upon the existing structure of DCNNs to include features such as bounding boxes. This differed from traditional DCNNs by being able to identify the location of an object in an image, rather than its mere presence.

In 2017, a state-of-the-art descendent of this previous research called Mask R-CNN was published within Facebook's AI research (FAIR) division. (39) A primary benefit of Mask R-CNN is the increased precision in object recognition by being able to tell if individual pixels are part of an object. Also, Mask R-CNNs are compatible with existing, large-scale training datasets such as the Common Objects in Context (COCO) dataset. This dataset consists of over 328,000 labeled images of everyday scenes built for use in object recognition research and gives computer vision algorithms valuable training data to recognize commonly seen objects like people, cars and trains. (40). These features of Mask R-NN allow for rapid deployment to object recognition tasks.

In computer vision Mask R-CNN has several distinct advantages over other algorithms. They have been extensively tested in many domains while maintaining a high level of accuracy. This extensive testing has led to the creation of a plethora of transferrable training data, easing the application of Mask R-CNN to new scenarios (40). Mask R-CNN is also invariant to changing environmental conditions in ways that traditional computer vision techniques e.g. (background subtraction (17–19), blob analysis (41)) are not. Finally, Mask R-CNN can continually improve its accuracy through back-propagated validation, using every successful classification as positive reinforcement for future classifications.

The development of faster and more accurate neural network architectures has led to an increase in practical applications. The detection and tracking of pedestrians using these methods have been extensively studied. (42) These research initiatives have used convolutional neural networks to track people for a variety of purposes which closely mirror the needs of trespassing e.g. autonomous driving (43–45) traffic safety (Szarvas et al.; M. and Sakai), and surveillance (46–51). The variance in the literature consists in the adjustment of variables of a convolutional neural network (number of layers, orientation of layers, application of study etc.) for maximal accuracy and quickest processing speed. Trespassing detection partially consists of tracking pedestrians on railroad property, therefore the methodologies outlined in the literature have many parallels to the railroad trespassing problem.

Many industries, including railroads, have used convolutional neural networks in other capacities. These applications range from airplane recognition in imagery (52) to the tracking of ships in ports (53) to roadway crack detection (54). Within the railroad industry, research by Gibert et al used convolutional neural networks to identify missing track components in inspection photos. (55)

1.4 Purpose of This Thesis

To address the challenges described, this thesis describes two AI algorithms to "watch" "recognize" and "understand" trespassing events using an existing video infrastructure. In addition, the second algorithm is coupled to a live alert system, which sends trespassing alerts to designated destination.

Specifically, this research aims to produce the following deliverables:

1) Develop a methodology for AI-aided trespassing detection and alert

2) Develop a practice-ready tool implementing the algorithm

3) Collect and analyze trespassing data to understand trespassing characteristics

1.5 Thesis Outline

In the introduction, the problems of trespassing in a railroad context, availability of video data and outline of the research are discussed. In chapter 2 the first AI-Aided trespass detection framework is described. The computer vision methods, data sources and results of the study are discussed. In chapter 3 the second AI-Aided trespassing detection framework is described. An analysis of the AI methodologies are discussed in concert with available video data and resultant characteristics of the research. This research work included in this thesis was carried out from January 2017 to August 2018.

1.6 Trespass Detection Framework Development

The main sections of this thesis, chapter 2 and chapter 3, describe two approaches towards utilizing existing video infrastructure to detect and analyze trespassing events. Each of these approaches were distinct in the video data analyzed and AI algorithm used. The transition from the first to second framework represent an improvement driven by peer review and industry professional feedback.

The first trespass detection framework, described in chapter 2, was developed to detect trespass events at a single grade crossing. Footage for analysis was provided by a railroad industry partner and had a duration spanning approximately 25 hours. The AI algorithm developed used an amalgamation of computer vision techniques, such as background subtraction, region of interest, Kalman filtering and moving pixel histograms. The combination of the features in this study resulted in a lightweight (low computation cost, fast analysis time) algorithm which was able to detect trespasses at the given location. However, there were several significant limitations to the developed program highlighted through discussions with academic peers and industry partners. Substantial reprogramming would be required for applying the algorithm to new locations limiting the flexibility of the framework. In addition, the analysis period of 25 was short and only two trespass events were captured in the study period. Lastly, the algorithm was offline, limited to the analysis of archival footage, a design decision based on the currently available video data. These limitations were rectified in the development of the second framework and initiation of a second trespass detection study.

The second framework, described in chapter 3, improved upon the limitations of the first framework. The new study included an expanded list of railroad video feeds that covered diverse infrastructure orientations, traffic densities and environmental conditions. The framework was modified to use a state-of-the-art AI algorithm called Mask R-CNN, which allowed for greater precision in trespasser detection and automatic differentiation of trespasser type and quantity. (Mask R-CNN) A summary of the key differences between the first and second frameworks can be seen in Table 1.

Table 1 Framework Feature Comparisons

	Framework 1	**Framework 2**
Video Data Source	Rail Industry Partner	Public Sources
Number of Locations	1	3
Video Type	Archival Only	Live or Archival
Analysis Duration	25 Hours	+200 Hours
Live Alerts	No	Yes
Computational Cost	Low	High
Anonymization	Manual	Automatic
Features Extracted	{Trespass Event} {Trespass Time}	{Trespass Event} {Trespass Time} {Trespasser Type} {Number of Trespassers}

The main difference between the two frameworks lies within the type of artificial intelligence algorithms used. The first framework used a series of computer vision algorithms (background subtraction, blob analysis, Kalman filtering and mapping of moving pixels) to understand trespassing events. The second framework used a deep convolutional neural network algorithm called Mask R-CNN to a greater effect. Each of these algorithms had several unique features and associated benefits and limitations. A summary comparing the two algorithms can be seen in Table 2.

Table 2 AI-Algorithms Comparisons

	Framework 1	Framework 2
AI-Algorithm	Background Subtraction, Region of Interest, Blob Analysis, Kalman Filtering & Mapping of moving pixels	Mask R-CNN, Region of Interest
Benefits	• Low Computational Cost • Fast Archival Review Speed (2% of Actual Duration)	• Ability to Recognize Objects • Ability to Differentiate & Count Multiple Objects • Invariance to Changing Environmental Conditions • Automatic Anonymization with Colored Masks
Limitations	• Requires Extensive Re-Configuration for New Applications • Limited Object Recognition	• Very High Computational Cost • Slow Archival Review Speed (Real Time) • Object Recognition Dependent on Training Dataset

Further details regarding the exact usage and results of each study can be seen in the respective chapters.

Chapter 2: Archival Trespassing Grade Crossing Video Analytics Framework

Zaman, A, X. Liu, and Z. Zhang. 2018. "Video Analytics for Railroad Safety Research: An Artificial Intelligence Approach." *Transportation Research Board* 97.

2.1 Objectives of Research

To make the analysis of railroad video data much less labor-intensive, this chapter develops a framework for utilizing AI technologies for trespass detection and the extraction of useful information from railroad big video datasets. This framework has been designed and implemented on video data from one grade crossing in New Jersey. The AI algorithm can automatically detect unsafe trespassing of railroad tracks. Specifically, this research aims to produce the following deliverables:

- Development of a general AI methodological framework for railroad big video data analytics.
- Application of the technology to a use-case, which is grade crossing trespass detection.
- Implementation of the AI algorithm into a computer-aided decision support tool that automatically processes big video data and outputs trespass video clips.

2.1.2 Knowledge Gaps

Currently, AI-driven big video analytics are still in an early stage in railroad safety research. Video analysis occurs largely on a manual basis. A customized AI algorithm would significantly expedite video analysis process.

2.1.3 Intended Contributions of This Chapter

This chapter intends to develop a unique, AI-aided methodological framework for video analytics that can be adapted to different application scenarios in which railroads need to analyze big video data in support of their safety decisions. Using an illustrative application in grade crossing trespass detection using surveillance camera videos, a systematic analytical procedure showing how AI can be developed and used to generate trespassing video clips is provided. The methodology can be adapted to other scenarios toward automated, video monitoring and analysis. Trespass data, which supplements accident data, provides additional useful information for understanding risky behaviors.

2.2 Artificial Intelligence Aided Railroad Video Analytics

There are a variety of resolutions, frame rates, opacities, and brightness levels in railroad video data. Each of these presents a challenge when training an AI to process and extract information from these data. There are several performance requirements for the AI in analyzing video data. First, it must accurately identify vehicles, trains, artifacts, shadows, and other objects. Second, the algorithm needs to be robust in diverse environmental conditions. This includes inclement weather (e.g. rain, fog, snow) and varying light conditions (twilight, nighttime, daytime). During the night those opacity levels change, and when vehicles drive by, headlights may cause a false detection. New opacity levels and extra checking techniques need be implemented to remediate this issue.

To address the above-mentioned challenges, a general AI approaches for video analytics, including background subtraction (24,41,56,57), blob analysis (58), and Kalman filtering (25,27,59–61) for potential application to railroad video analysis is introduced (Figure 2). These techniques isolate the moving objects and track their movement. Background subtraction is particularly useful because most cameras are static (e.g. those in stations, at grade crossings, or on bridges). The removal of the background allows for the isolation of the moving objects (humans or vehicles) in the frame. Each pixel is derived in color scale and averaged over several frames as appropriate to the application. This is important as the environment causes light and vegetation to shift slightly, and an average value with inbuilt tolerances allows for a more dynamic background. The subtraction occurs on a frame-by-frame basis as well, where each color-scaled pixel is subtracted from the learned background, resulting in a binary mask. In another approach, an AI algorithm establishes pixel ranges known as line of interest or region of interest, which aid in the counting and recording of objects' behavior as they traverse the frame. By isolating part of the frame, less pixel-to-pixel calculations are required, which is particularly useful in high-resolution footage where the number of pixels is large. Finally, Kalman filtering can predict the movement of objects. This can also aid in the classification of specific types of objects that are tracked. With the values of objects' sizes and acceleration obtained and/or predicted, the differentiation between vehicle and pedestrian or vehicle and train can be ascertained (25).

These techniques—removing the stationary background, identifying the moving objects, determining if they are traversing an area of interest, and removing the non-conforming objects—establish a framework for AI-aided railroad video data analytics. Furthermore, developed AI-based techniques should be trained to test and verify its robustness. A training program for an artificial intelligence application for railroads would require the development of an initial algorithm with established environmental parameters. This draft algorithm analyzes a training set of data, comparing the algorithm's results to the knowns. A successful verification would require the algorithm to correctly "see" images of trains and pedestrians independently from the background, using techniques such as background subtraction (24). The AI can then be retested with various weather conditions and diverse daylight conditions, such as dawn, day, dusk, and dark. After undergoing this training, an AI Application can capture the images and moving paths of trains and highway users, such as cars, pedestrians, bicyclists, under a wide array of external conditions. Then the AI tool can record critical video information automatically, which is compiled into a database for future study.

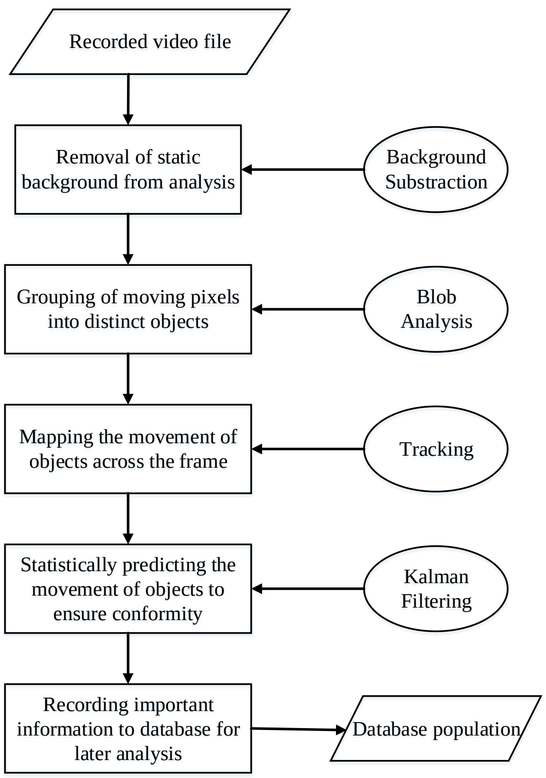


Figure 2 General AI framework for railroad video data analytics.

2.3 Application to Grade Crossing Trespassing Analysis

Grade crossing trespassing accounts for a large number of incidents and fatalities annually (61). An AI algorithm was developed and implemented with the data based on one grade crossing in New Jersey. The CCTV video footage of this grade crossing was obtained, and a customized AI algorithm was developed to detect trespassing. A trespass event occurs when a pedestrian or vehicle traverses the crossing while the red signal is on. Almost all prior studies in the field of grade crossing safety have focused on using accident data (21,62), without accounting for a larger number of trespasses that share similar behavioral characteristics but (fortunately) did not cause any harm yet. The following section details the process of using AI to automatically detect trespasses from grade crossing video data. The general methodology can be adapted to other use cases in the future.

2.3.1 Algorithm Flow Chart

This AI reads the video file looking for a red signal, processes the image (details will be presented later), and evaluates whether a trespass has occurred. Detailed analytical steps are presented below.

Step 1 Reading Video Frames Sequentially

The first step of the algorithm is to start reading the video file frame by frame. During this reading, the prime objective is to determine if the active signalized crossing light has been triggered. To increase processing speed, a frame-skip segment is included, which advances the reading in 10-second intervals and stops when a red light is detected; this is practical in this application because the duration of a stop signal is greater than 10 seconds for this grade crossing. Frame-skip algorithms also allow for adaptability to high frame rate video and reducing analysis time.

Step 2   Detection of Stop Signal

After a frame has been isolated, the stop signal (red signal) is recognized in that frame. A checking of the red pixel values in the small area of the frame where the signal lies determines its status (Figure 3). The user can configure the location and the opacity threshold for this application. If a stop signal is detected, the algorithm performs a frame-by-frame check backwards to determine the beginning of the stop signal. Then, the subroutine of trespass detection is activated.

Figure 3 Stop signal under day and night conditions.

Step 3   Background Template Learning

The trespass detection subroutine follows several steps. The first is to learn and subtract the background template at the beginning of the stop signal. Non-moving objects are captured in the field of view at this time. For each stop signal that is encountered in the video, a new background is learned. This overcomes the challenge of the gradual changing of light levels throughout the day. Other environmental conditions such as passing rainstorms, parked cars in the background and others are also captured in the background template learning (Figure 4).

Figure 4 Computer-recognized background using training data.

Step 4 Objective Tracking

Moving objects are detected in the foreground with the background subtraction technique (*13, 23-25*). With background subtraction, the total number of moving pixels can be tracked and recorded from frame to frame; this detection continues until the red signal turns off.

Step 5 Identifying Trespasses

After the previous steps, the algorithm identifies a trespass event based on the total number of moving pixels. One main challenge here is to recognize and remove the "noise" from moving pixels of a train. It was noted that the number of pixels that a train occupies in the foreground during a crossing is much larger than that of highway users (e.g., a pedestrian or a vehicle). Therefore, a proper threshold can be established to separate trespassing objects from trains. If a trespass is detected, all frames of the red signal are extracted to a video file for further review. After stop signal processing concludes, the algorithm skips five minutes and continues the analysis from Step 1. This five-minute skip further reduces processing time and does not compromise the accuracy of the analysis since no stop signals re-occur within this short interval in this case study. These parameters can be easily changed for different applications.

2.4.2 Results

The goal of our algorithm is to complete the analysis much faster and with equal or greater accuracy than manual reviewing. In this case study, the processing of the video took roughly 2% of the total video duration to complete. This duration is highly dependent on the number of stop signals encountered. Two trespass events were detected on a 25-hour video dataset, covering three different days. The processing time for this video was less than 40 minutes. Detailed summary is listed in Table 1.

Table 3 Results for AI-Aided Detection of Trespasses

Date	From	To	Duration (Hours)	Red Signals	Trespasses
Day 1	08:00	15:00	07:00	21	0
Day 2	00:19	09:00	08:41	20	2
Day 3	12:00	21:00	09:00	26	0
TOTAL			24:41	67	2

The algorithm's output showed two trespass events occurring within a single stop signal in the morning of one day. In the first trespass, before the train arrived, two pedestrians entered the grade crossings while the stop signal was active (Figure 5a). Five seconds after the two pedestrians crossed the track, the train arrived. The second trespass occurred when a cyclist, who had stopped at the deployment of the arm gates and stop signal, crossed after seeing that the train was gone, without waiting for the signal to be deactivated (Figure 5b).

(a)

(b)

Figure 5 Two trespass incidents detected by the AI algorithm.

The results of this study epitomize two different types of highway users and two typical non-compliance behaviors. The two pedestrians perceived the timing of train arrival from their judgment and were confident with their ability of crossing the track before the train arrived. The second case illustrates the assumption that no second train would cross, despite the presence of multiple tracks and the continuing of the signal. Both trespasses represent risky behaviors with potentially catastrophic consequences, which have been seen in the past accident data (3,62).

2.4 Web-Based Decision Support Tool (AI-Grade)

The AI algorithm described above was implemented into a web-based decision support tool called "AI-Grade" (Figure 6). The web-based AI-Grade streamlines the automatic processing of railroad grade crossing data through the following steps:

- Step 1 – Login in the application website
- Step 2 – Select the video file that needs to be analyzed and enter the user's email address.
- Step 3 – Click "Submit" and the processing will begin.
- Step 4 – Once processing is completed, users will receive an email that provides the cropped trespass video, if any.

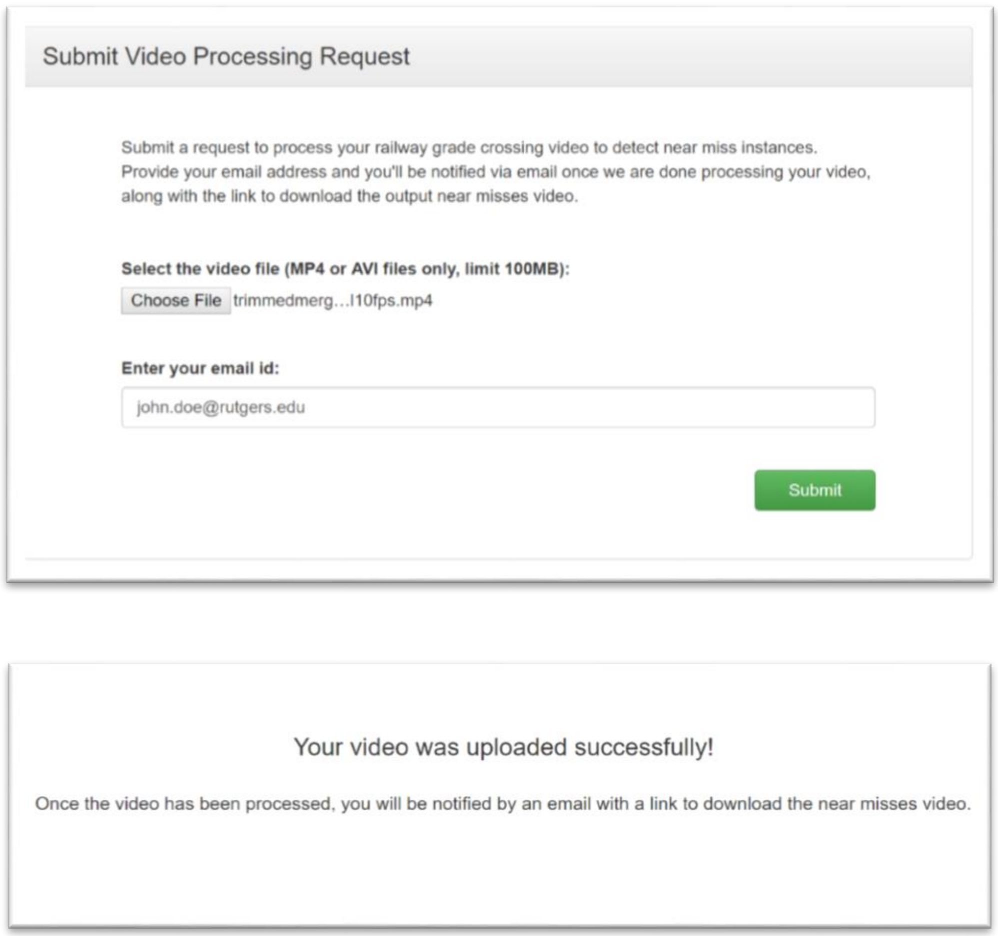


Figure 6 AI-grade decision support tool user interface.

2.5 Tool Validation

To ensure the usefulness of this AI tool, results must be accurate and achieved faster than via manual processing. A validation of this criteria was completed using the collected video data. In terms of accuracy, there are four possible results: 1) an illegal trespassing occurs, and a detection is recorded (correct); 2) no illegal trespassing occurs, but a detection is recorded (false positive); 3) an illegal trespassing occurs, but there is no detection (false negative); and 4) there is no illegal trespassing and there is no resulting detection (correct).

Table 4 Tool Validation Outcomes for Trespass Detection

	Trespassing	No Trespassing
Detection	100%	0%
No Detection	0%	100%

For comparison, the footage was manually reviewed and the results were compared to the output of AI-Grade. To date, AI-Grade is 100% accurate without any false positives or negatives (Table 2). In addition, the AI program completed processing the 25-hour video within 40 minutes, totaling 2% of the video time. We are further developing and training this algorithm using more video data (e.g. one-year data) from our industry partners. Ultimately, we hope to design a tool for real-time analytics of video data in support of railroad safety decision-making.

2.6 Contributions to Research and Practice

2.6.1 Contribution to Academic Research

This chapter describes an Artificial Intelligence technological framework for automatically detecting trespasses at grade crossings. Before the advent of AI technology, it was not practical to collect diverse information (e.g. the time, type, and environmental conditions surrounding illegal trespassing), from big video data because of an inordinate amount of person-hours required for the acquisition of such information. The expected contribution of this research to railroad safety parallels what the FHWA-sponsored study on Naturalistic Driving did for highway traffic safety, which used sensors to collect vehicle movement and driver attention data and used this information for highway safety analyses (63). Similarly, we aim to empower AI to analyze a large amount of railroad video data for better understanding human factors in various application scenarios.

2.6.2 Contribution to Practice

The practical contribution of the AI framework is its applicability to this and other scenarios in the rail industry (e.g. inside cabs, at stations, rail yards, and on platforms). This information will help railroad agencies make decisions regarding the allocation of limited safety budgets. AI can be trained to recognize a variety of environmental factors (e.g. weather, track geometry, the population surrounding rail facility), as well as risk-prone human behaviors (e.g. illegal trespassing, operator fatigue). Further, AI can be developed to quantitatively measure the association between risky behaviors and their influencing factors. These results enable development of proactive strategies to prevent or reduce trespasses or incidents in railroad system, thereby improving its safety. Additionally, the implementation of this framework has a low cost. It utilizes an already existing video recording infrastructure and has no additional hardware costs.

2.7 Conclusion

This chapter proposes the use of a customized artificial intelligence algorithm for automatically analyzing railroad video data to solicit useful information for understanding human behavioral characteristics. Different aspects of trespassing events can be extracted using this framework, which provide different levels of information relevant to different parties within the railroad industry. Trespasser data, aggregated en-masse through this framework, could allow for greater understanding into human behavior and inform railroad safety solutions to this critical problem. For example, if it is found that trespassing at a grade crossing occurs in a concentrated time period throughout the day, the presence of a police officer for a limited time could deter a large portion of potential trespasses. (64)

In a larger view, acquiring data on the number of trespassing events at grade crossings can provide a more complete picture of the relative riskiness of different locations. Studies on the accident risk at grade crossings use accident data, not trespassing data, to judge the relative danger of each location. (20,21) Using the AI-driven framework outlined in this chapter valuable information could be gathered to inform a more efficient allocation of limited safety budgets to save the greatest number of lives.

An example implementation and decision support tool are developed based on grade crossing surveillance video data. In the study period, our AI algorithm correctly detects all the trespass events associated with unsafe trespassing of the studied grade crossing. This algorithm was able to understand both the condition of the environment and the behavior of humans in the frame. The subroutine which analyzes the flashing light extracts important information about the state of the grade crossing and the presence of an approaching train. Additionally, the framework determines if pedestrians and vehicles are crossing the region of interest only during periods when they should not, differentiating between legal and illegal crossings.

Trespass data can be used for developing safety strategies to prevent the occurrence of risk-prone behaviors and resultant accidents. This research indicates the promising applications of AI to other research areas in railroad industry in the future, such as in-cab video analysis for distraction detection or security surveillance in railway stations. Prompted by industry feedback, several improvements to the current framework are required to implement this framework in the field. To validate the accuracy and prove the ability of this framework to provide high quality data to inform risk analyses a larger video dataset must be reviewed. This dataset must include new locations, environments, infrastructure orientations and possibly, more trespassing events. The combination of those factors would prove the algorithm's value to the industry and ability to inform safety decisions.

Chapter 3: Generalized Live Video Trespassing Video Analytics Framework

Zaman, A, B. Ren, and X. Liu. 2019. "Artificial-Intelligence-Aided Automated Detection of Railroad Trespassing via Big Video Data Analytics." *Transportation Research Board* 98. (SUBMITTED)

3.1 Objectives of Research

The goal of this chapter is to create an improved AI framework that can analyze live video feeds in real time or analyze archival footage to gather useful information on trespassing for railroad safety purposes. Specifically, this study aims to yield the following deliverables;

1) Develop a methodology for AI-aided trespassing detection and alert

2) Develop a practice-ready tool implementing the algorithm

3) Collect and analyze trespass data to understand event characteristics

Figure 7 shows a conceptual view of the system, where an AI algorithm can send live alerts to designated personnel by analyzing and identifying trespassing events in live CCTV feeds. Additionally, trespassing events are also recorded in a trespass database containing video and associated metadata (time of day, type of trespassing, type of trespasser, etc.).

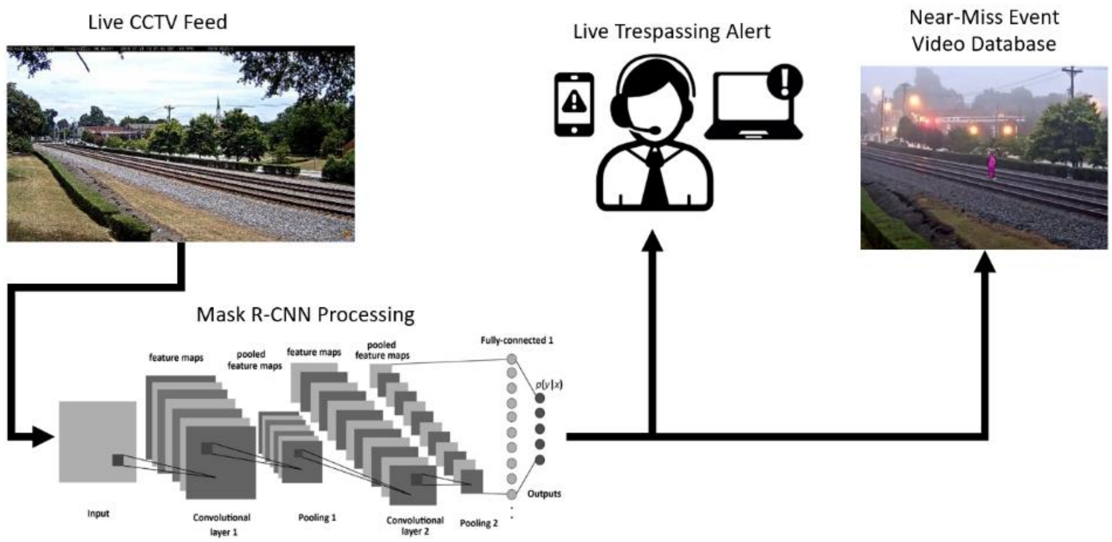


Figure 7 Conceptual Trespasser Detection & Alert System using Artificial Intelligence

3.1.2 Knowledge Gaps and Intended Contributions

Currently, AI-driven video analytics are new to the railroad industry and the monitoring of railroad live feeds occurs largely on a manual basis. This research aims to narrow this gap by providing an AI-aided trespass detection framework to collect trespassing data that informs engineering, education and enforcement strategies for trespass prevention.

3.2 AI-Aided Trespass Detection Framework

Detection of trespassing events in video feeds have many challenges. There are a wide variety of configurations, environmental variables and technical features of live data streams of railroads. An AI built for trespass detection must have several fundamental performance qualities. It must accurately identify pedestrians and vehicles within the frame, unhindered by video artifacts, shadows and other distortions. Secondly, the AI must maintain accuracy in diverse environmental conditions e.g. (rain, snow, day, night, fog etc.). Finally, when analyzing a live video stream, the AI must be able to process the frames quick enough to maintain a fast response time to possible trespassing events.

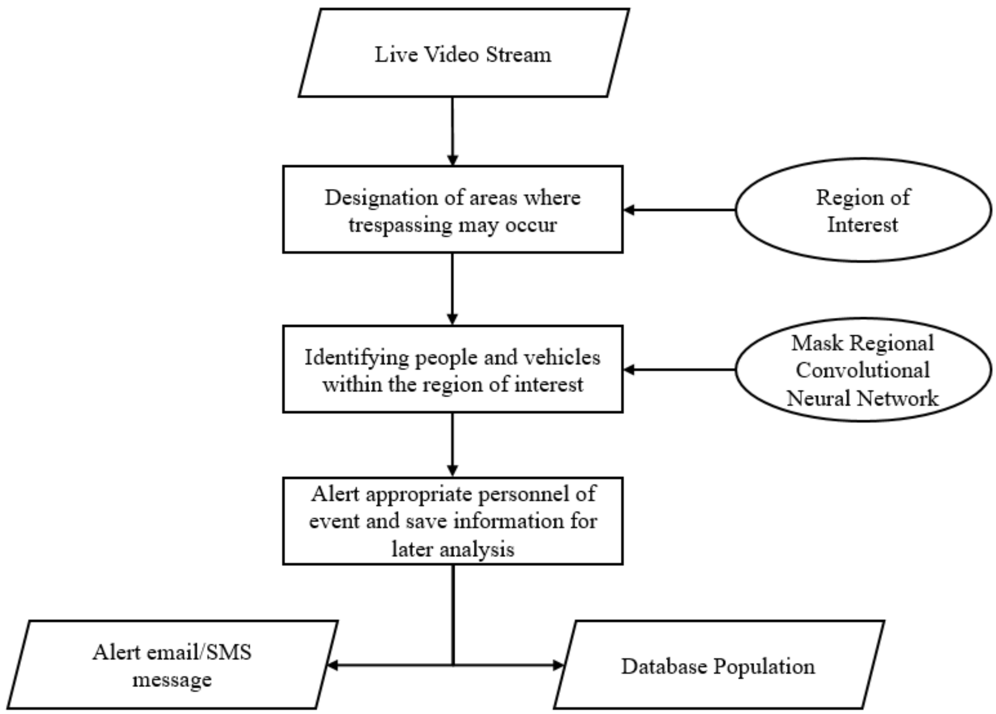


Figure 8 General AI Framework for Railroad Trespass Detection

To address these challenges a generalized AI framework for trespass detection which utilize the combined techniques of region of interest (27) and Mask R-CNN (39) is proposed (Figure 8). After defining the ROI, the Mask R-CNN analyzes frames of the live video feed. If an unauthorized person or vehicle enters the ROI an alert would be sounded and relevant trespassing data recorded to a database for later review and analysis.

A key part of Mask R-CNN performance is the training dataset which allows it to recognize objects. The COCO dataset, consisting of many labeled images of everyday scenes built for use in object recognition research, was utilized for this purpose. It was selected because of its depth (330,000 Images), diversity (80 object categories) and timeliness through its continual growth and refinement. (40) Additionally, the COCO dataset includes pre-generated boundaries around recognized images allowing for better object recognition. By providing the Mask R-CNN with this dataset it can recognize people, cars, trains and other objects within the ROI.

If an illegal object is detected within the ROI a subroutine of the AI will execute two simultaneous commands. Firstly, an alert SMS text or email is relayed to a pre-determined user. This can be a railroad safety official who can decide of possible reparatory actions. Secondly, a clip of the trespass incident is recorded and metadata e.g. (object detected, time, location, video file name etc.) is stored in a trespass event database. This metadata is automatically generated by the AI demonstrating that context of the image can be extracted and interpreted. Trespassing data can provide valuable information about hazardous environments and behaviors that lead to trespassing events which can inform education, enforcement and engineering strategies for trespass prevention. Additionally, the aggregation of these trespass events has the potential to enhance railroad risk analyses in the future.

The AI framework should be trained to verify its accuracy by having the algorithm analyze a video dataset with established results. Comparing the results of the dataset to the known number of trespasses verifies the AI algorithm's performance. Additional datasets, including varying environmental conditions, should be tested with the algorithm to verify its performance under diverse circumstances.

This framework is intended to be implemented on live streams of railroad property, which lead to the consideration of several concerns which will be addressed in our ongoing work;

- Ethics – Ensuring the privacy of individuals captured in the analysis;
  - Plan: Implement colored masks over detected people and vehicles with Mask R-CNN.
- Economics – Balancing cost & benefits of the technology;
  - Plan: Perform costs analysis to ensure the most effective technological solutions have been utilized.
- Accuracy – Continually improving accuracy with growing database;
  - Plan: Analyze false alarms and missed detections & incorporate solutions into the AI.
- Demand – Adding data types and metrics as per stakeholder request;
  - Plan: Add relevant contextual metadata as requested.
- Support – Responding to system failures and correcting errors;
  - Plan: Continual communication is maintained with industry partners to meet operational needs.
- Adaptability – Ensuring the ability to perform under unforeseen or untested scenarios;
  - Plan: Expand testing and training data to new scenarios and to ensure consistency in any environment.
- Availability – Maintaining access for stakeholders;
  - Plan: Develop easy-to-use dashboard to view trespass data and analyze new data streams.

3.3 Trespass Detection Applications

The combination of grade crossings and other trespassing events make up most casualties in the railroad industry (2,3). Almost all prior studies in the field of trespassing and grade crossing safety have focused on the accident data (21,65) without considering events that do not result in an accident. These trespasses share similar behavior characteristics to accidents, with the exception that they do not result in immediate harm. Repeated trespasses have the potential to lead to severe consequences and learning from these incidents can inform proactive risk management strategies in the future.

This framework was tested on two different safety-critical scenarios; grade crossings and non-grade crossings. Active warning grade crossings alert vehicles and pedestrians when they are not allowed to cross the tracks. Therefore, an AI algorithm must be able to differentiate between legal and illegal passes. On a non-grade crossing location, this distinction does not need to be made, as all crossings are deemed illegal, except for authorized railroad personnel. This categorization represents the two fundamentally different types of locations where trespassing occurs and was able to be analyzed by the same generalized trespass detection framework. Passive grade crossings, which lack active signalization like lights, arms and gates, were not addressed in this study due to lack of available video coverage of these locations.

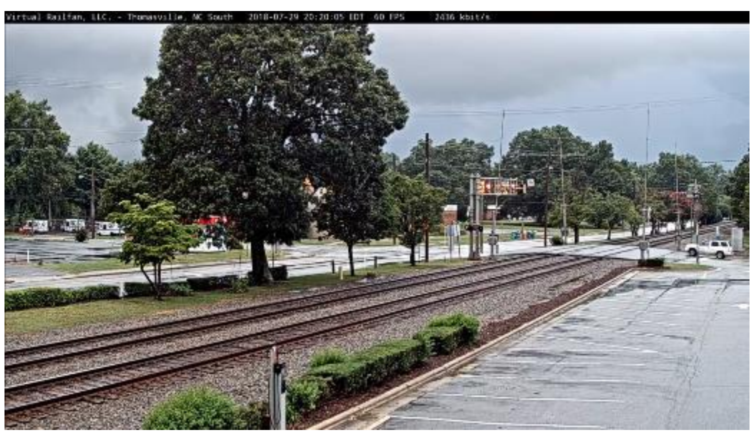
In our preliminary investigation of potential data sources to test this framework it was discovered that there exists a dearth of publicly available camera streams of railroads. These streams were originally intended for railroad enthusiasts to view for entertainment, but provide a high quality (high resolution, high frame rate, reliable up time, etc.,) data source for railroad safety research. To select an appropriate stream several variables were searched for;

- Clear view of signal lights for grade crossings
- Urban population to increase the chance of trespassing events (66)

With these factors, three streams were identified for analysis. Figure 9 shows a typical view of the locations.

(a)

(b)



(c)

Figure 9 (a) Selected Grade Crossing Stream (b) Selected First Non-Grade Crossing Stream (c) Selected Second Non-Grade Crossing Stream

The selection of one grade crossing and two non-grade crossings was based on several reasons; 1) availability of video streams with a clear view of signal lights 2) demonstration of the flexibility to different trespassing environments. In the future, it is planned to expand the search for live video feeds to examine a greater number of grade crossings and non-grade crossings alike.

3.3.1 AI Algorithm Flow Chart

The AI will parse the video live stream, prompt the user to identify the ROIs within the frame, detect whether people or vehicles are in the ROI and send alerts if a trespass has occurred. The detailed steps are presented below. The algorithm can analyze both grade crossings and non-grade crossings based on the activation of a single subroutine which demonstrates the framework's adaptability to different trespassing use cases throughout the railroad industry with no adjustments. This special subroutine detects the activation of flashing lights that indicate an approaching train.

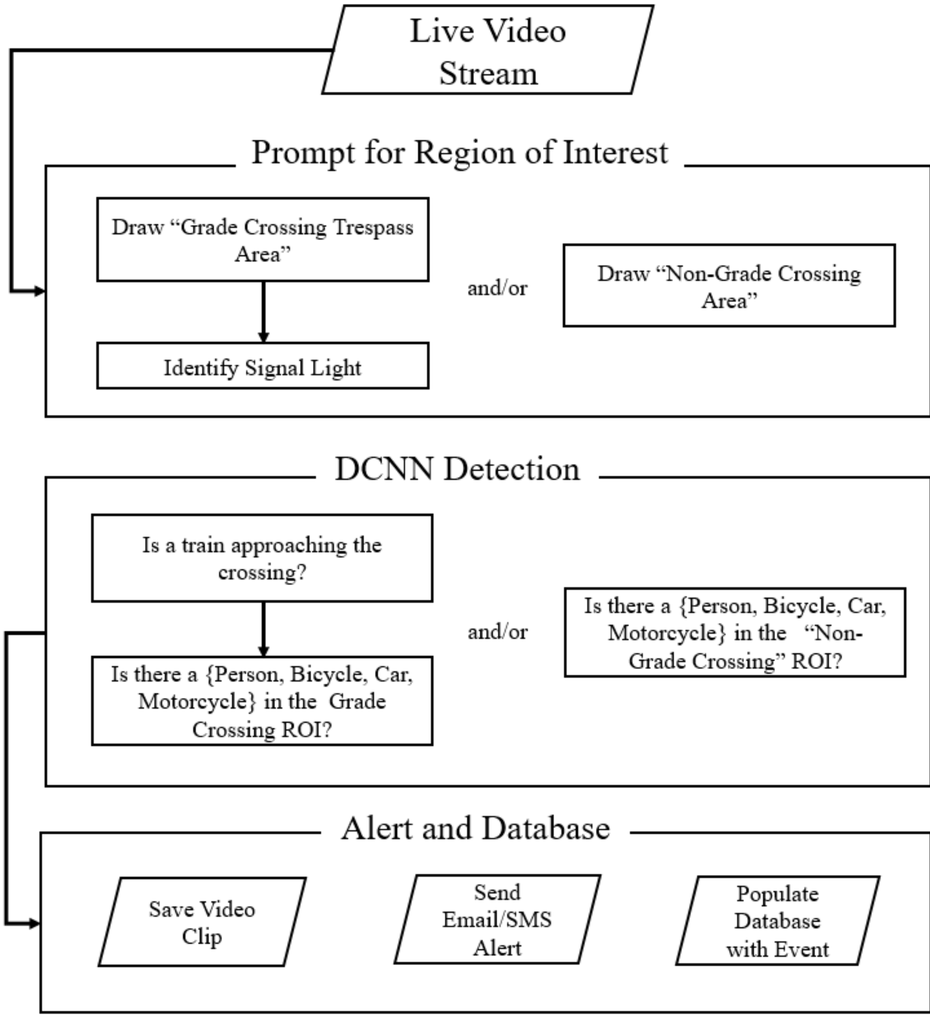


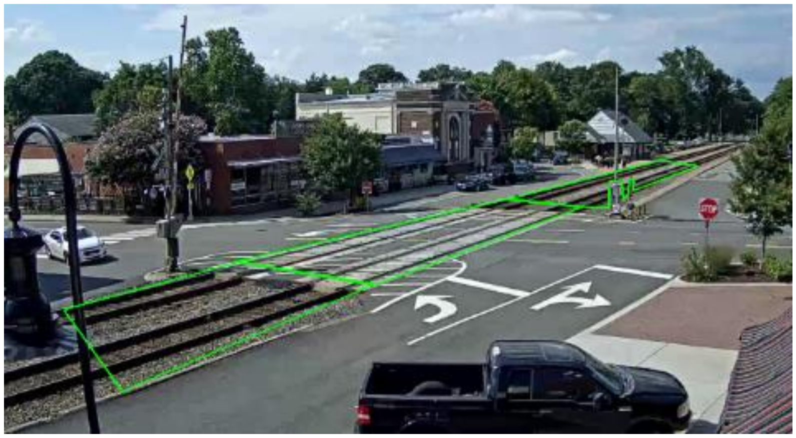
Figure 10 Detailed Trespassing Framework for Railroad Trespassing (Including Both Grade Crossing and Non-Grade Crossing)

Step 1 Parsing the Live Stream

The first step of the AI is to establish a connection to the live stream of the selected location. After raw video data is provided, for example via internet live stream, the program will proceed to step 2.

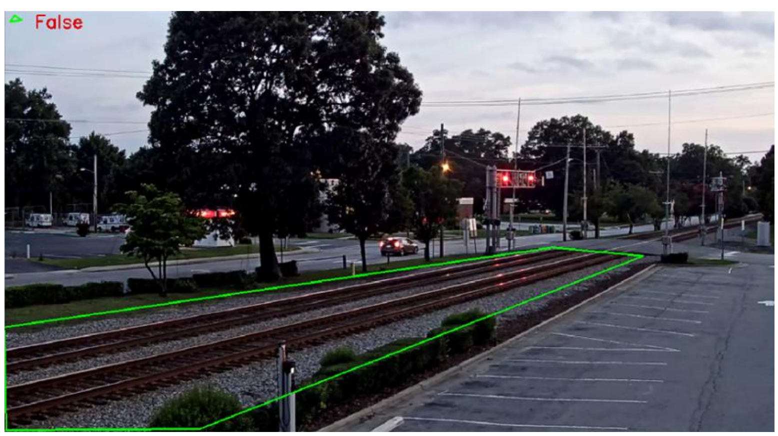
Step 2 Draw Region of Interests

The second step of the program is to identify the region(s) of interest. A user will be prompted with a static image of the video feed and the user can sequentially select the outer limits of the trespass area. The borders of the ROI will be represented by a green line and can be closed by selecting the first point. Multiple ROI's can be identified in the same frame and a differentiation between "non-grade crossing" and "grade crossing" can be made. The difference between these two is that any object (person, motorcycle, bicycle, car or truck) except authorized railroad personnel detected within the "non-grade crossing" ROI will be deemed illegal and trigger an alert. Conversely the "grade crossing" area will only trigger an alert if the algorithm detects that the signal lights are active.



(a)

(b)



(c)

Figure 11 (a) ROI of Grade Crossing Stream (b) ROI of First Non-Grade Crossing Stream (c) ROI of Second Non-Grade Crossing Stream

Step 3 Trespass Detection

The third step in the algorithm utilized the Mask R-CNN framework (39). Each frame analyzed was checked for objects within the selected ROI. If a grade crossing ROI was identified a subroutine will actively check for the initiation of a crossing signal light. When that light activates people and vehicles within the ROI are deemed trespassing. Both freight and passenger trains are also identified by the algorithm but deem them as legal occupiers of the ROI and therefore do not trigger alerts. A limitation of the algorithm is its current inability to differentiate between authorized railroad personnel and trespassers. In future research, we aim to resolve this by providing the Mask R-CNN with training data to filter out authorized railroad personnel and workers based on the unique characteristics of their attire. In the current framework, these events are manually filtered out.

Step 4 Alert and Database Population

The final step of the AI is twofold; send an alert text message or email to a designated user and record the trespassing event video and metadata to a database. The alert text messages or email can be directed to railroad safety officials for immediate action. The database contains information on time, object detection, identified zone (grade crossing vs. non-grade crossing) and name of the associated video file.

3.3.2 Al Development and Testing Process

To ensure that this AI achieved the highest accuracy and minimized the number of missed detections and false alarms a three-part training and testing plan was executed (Figure 12). The first step of this plan was the initial development of the AI using several hours of training data. This training data was acquired by recording the live stream of the selected grade crossing location for a duration of 9 hours, capturing diverse environmental and traffic conditions. The training data was manually inspected to establish a known quantity of trespasses. The program then analyzed this footage and modifications were made to the program until 100% accuracy was achieved.

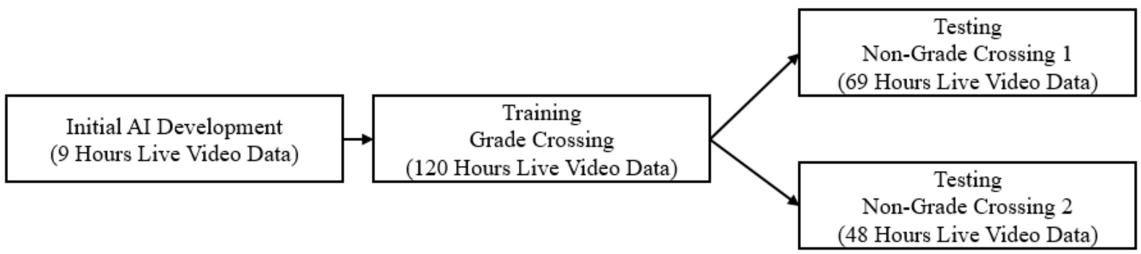


Figure 12 Algorithm Development and Testing Flowchart

The second step of this development process was the execution of a longer training period of the same grade crossing used to initially develop the program. This training phase differed from the initial one because the number of trespasses was not known beforehand but was acquired through meticulous manual reviewing of archival footage of the live stream. False positives and missed detections during this 120-hour analysis were identified, the AI was modified, and the archive was re-analyzed by the AI to ensure any problems had been resolved.

The third and final step of this analysis was to test the AI on two new locations. Two non-grade crossings were selected for this portion of the analysis and reviewed a cumulative 100 hours of live video. These locations were selected due to the availability of high quality video streams that met the previously established criteria. This final step of implementing the program on two completely new locations shows that the algorithm developed in this study is generalized and can accurately identify trespassing on video feeds throughout the railroad industry without significant modification.

3.3.3 Grade Crossing Results (Training)

During the 120 hours of live footage of the grade crossing between July 19th 2018 and July 25th 2018, 145 positively identified trespassing events reported via the alert system. The analysis period included a multitude of varying environmental conditions including heavy rainfall, fog and many day/night cycles. The AI was automatically able to differentiate between the type of trespasser and Figure 13 shows a breakdown of the results acquired during the analysis period.

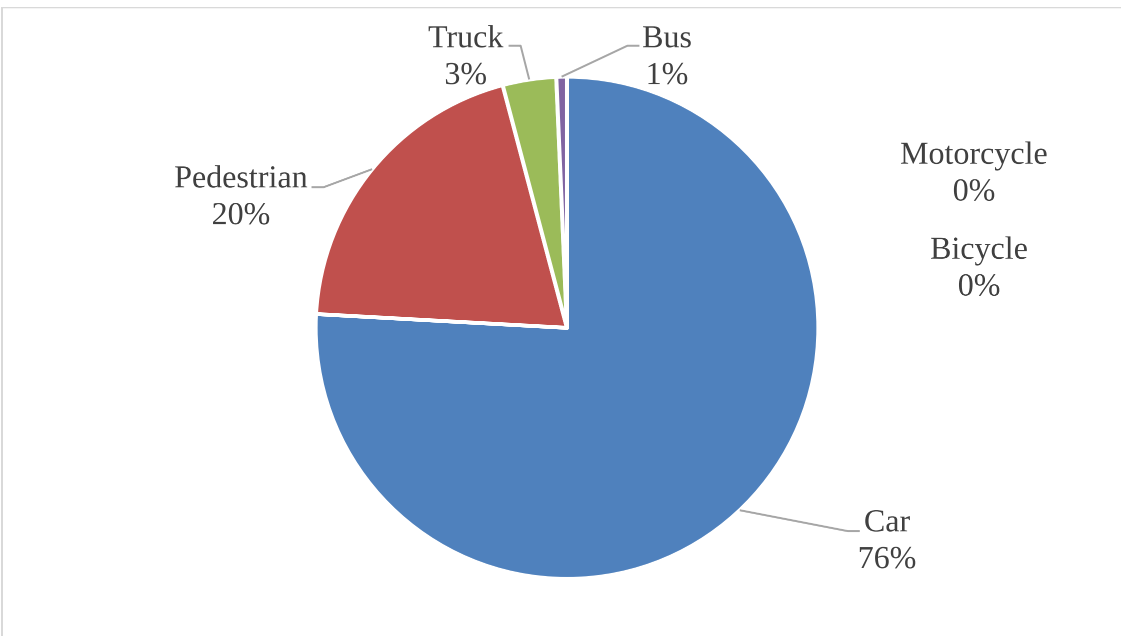


Figure 13 Distribution of Grade-Crossing Trespasser by Type

A summary of the study periods and detected violations can be seen in Table 5. While the training period spanned seven days, not all hours of the day were analyzed by the system. This was due to combination of several factors. Firstly, the framework was stopped for planned modifications to the program as segments of archival footage were reviewed and errors identified. The system would be taken offline until the fix could be applied and the archival footage of the errors rerun to ensure 100% accuracy. Secondly, outages at the stream's source due to weather and network connectivity issues prevented continuous analyses in several cases.

The number of fixes required to ensure optimal accuracy declined throughout the study. From July 22nd, 2018 forward, minimal debugging was required and the testing phase was initiated. To ensure the validity of the accuracy of the program the testing phase continued for three more days to ensure that no further errors would occur and capture as much information as possible for later analysis. A full listing of the trespassing events and corresponding video files can be seen in Table 8 Appendix – Framework 2 Grade Crossing Study Results with Reference Video.

Table 5 Summary of Trespassing Events during Grade Crossing Study

Date	From	To	Duration (Hours)	Violations: Car	Pedestrian	Truck	Bus	Bicycle	Motorcycle
7/19/2018	18:53	23:59	5:06:00	0	1	0	0	0	0
7/20/2018	9:23	21:22	11:59:00	27	6	2	0	0	0
7/21/2018	9:35	20:18	10:43:00	29	6	2	0	0	0
7/22/2018	0:48	23:42	22:54:00	29	3	0	0	0	0
7/23/2018	0:08	23:42	23:34:00	10	5	0	0	0	0
7/24/2018	0:08	23:59	23:51:00	11	5		0	0	0
7/25/2018	0:21	22:22	22:01:00	4	3	1	1	0	0
		Total Time	120:08:00	110	29	5	1	0	0
		Total Events	145	75.86%	20.00%	3.44%	0.68%	0.00%	0.00%

The most common type of violation witnessed in this study at the grade crossing was the passage of vehicles while the signalized intersection lights were activated. 116 events of this kind were detected making up 80.00% of all detected trespassing events at this location. Figure 14 shows several typical detected examples of this. The color overlay of the vehicle was generated automatically by the AI and indicates a recognized object. The masking also preserves the privacy.

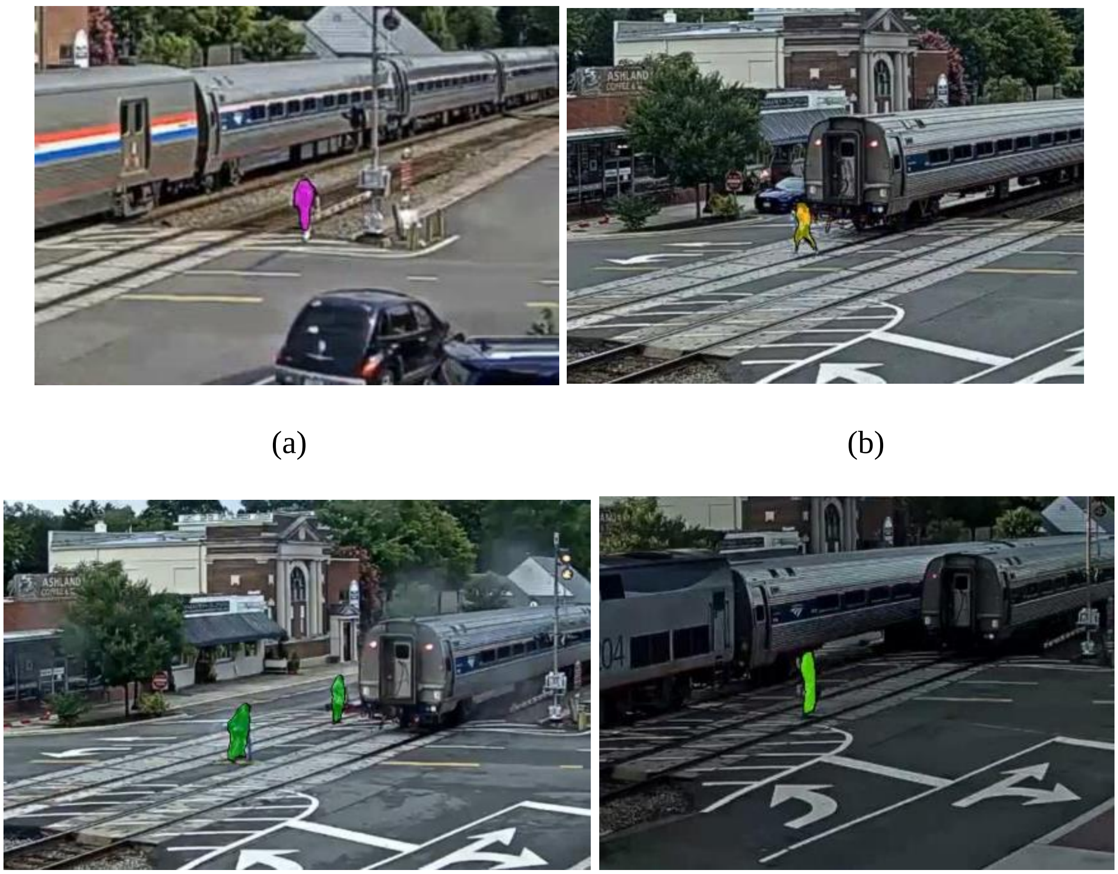
(a)

(b)

(c)

Figure 14 (a) Vehicle Driving Around Deployed Gates from Far Roadway (b) Vehicle Driving Around Deployed Gates from Near Roadway (c) School Bus Crossing as Gates Are Closing

The second most common trespassing events witnessed in this study were the illegal traversal of pedestrians while the active signalized gates were down. 29 events of this kind were detected making up 20.00% of all totally detected trespassing events at this location. Figure 15 shows several typical detected examples of this. The color overlay of the individual represents a recognized object by the AI.



(a) (b)

(c) (d)

Figure 15 (a) Pedestrian Walking Behind Gates (b) Pedestrian Crossing Behind Train (c) Multiple Pedestrians Crossing Behind Train (d) Pedestrian Waiting on Railroad Tracks

Both event types represent two typical non-conforming behaviors at grade crossings. For the drivers and pedestrians which traverse the crossing while the gates are lowering have the confidence that they have enough time to traverse the intersection before the train arrives. Individuals who crossed the intersection while the gates were raising assume that the crossing is now safe, disregarding the possibility that a second train may be approaching and will reactivate the gates. Both these trespass events have potentially catastrophic consequences which are represented by the multitude of casualties and fatalities at grade crossings (2,3)

These events were recorded to a local trespass database and if expanded, commonalities between trespassing behavior can be understood. If data gathered by this AI indicates trends, such as increased trespasser activity during regular time periods during the day, the presence of law enforcement may deter a large portion of illegal behavior. (64) In another example, if at the selected grade crossing it is discovered that most trespasses occur from a roadway direction, the installation of additional active signalization and barriers to that direction may mitigate excessive crossing. (64) In the future, expansion of this research to more locations and the aggregation of a large trespass database could highlight trends and inform solutions to the trespassing problem.

An additional feature of the Mask R-CNN (39) is its ability to automatically anonymize trespasser. Within the United States privacy in big data is of paramount concern. (67,68) This is verified by surveys conducted where 88% of Americans stated that they “do not wish to have someone watch or listen to them without their permission” and 63% of respondents “feel it is important to be able to go around in public without always being identified”. (30) The overlay of colored masks on detected trespassers prevents the identification of the induvial. Similarly, masks over vehicles obscure the license plate sufficiently to prevent identification, therefore maintaining the privacy of the driver.

3.3.4 Non-Grade Crossing Results (Testing Phase)

In the final portion of the study two completely new locations were tested by the AI to demonstrate the flexibility of this algorithm to different trespassing scenarios. On the first non-grade crossing location the AI analyzed 69 hours of live footage between July 21st 2018 and July 27th 2018. During this period, 7 trespassing events were recognized by the AI under several distinct environmental conditions, including rain, fog (Figure 16a), nighttime (Figure 16b). During these times, the AI was able to correctly identify trespassers despite the sub-optimal detection conditions. A full listing of the trespassing events and corresponding video files can be seen in Table 9 Appendix – Framework 2 First Non-Grade Crossing Study Results with Reference Video.

Table 6 shows a summary of the trespassing events captured throughout the first testing phase. The start and end times for each study period were inconsistent due to network connectivity issues at the stream source. There is a several day overlap with the first grade crossing study, but this was due to the limited number of errors and debugging required at this point in the study. The accuracy was deemed high enough to confidently initiate the first testing phase.

Table 6 Summary of Trespassing Events during First Non-Grade Crossing Study

Date	From	To	Duration (Hours)	Violations: Car	Pedestrian	Truck
7/21/2018	14:05	20:23	6:18:00	0	0	0
7/22/2018	11:38	19:23	7:45:00	0	1	0
7/23/2018	0:52	20:58	20:06:00	0	3	0
7/24/2018	6:00	22:30	16:30:00	0	2	0
7/25/2018	5:59	23:59	18:00:00	0	1	0
		Total Time	68:39:00	0	7	0
		Total	7	0.00%	100.00%	0.00%

Even though only pedestrians were detected during the study period, the algorithm would have been able to detect vehicles. These could potentially appear in extreme trespassing cases or when railroad maintenance vehicles enter the cameras field of view. This version of the framework was designed with the explicit intention to have generalized trespassing detection capabilities. This allows for the framework to be quickly deployed to diverse camera feeds with different infrastructure, while still maintaining high accuracy in detection and extraction of useful information.

(a) (b)

(c) (d)

Figure 16 (a) Trespasser Detected Crossing in Foggy Weather (b) Group of Trespassers Detected at Nighttime (c) Trespasser Detected Before Crossing (d) Trespasser Traveling Within Railroad Property

To date, the AI is 100% accurate (no false positives, no false negatives) at this location. Most of the trespasses detected at this location show individuals walking along the railroad tracks, instead of the sidewalk on the roadway to the north of the camera's view. It is unclear why these individuals made the choice to trespass on railroad tracks, but the aggregation of these events can inform proactive strategies towards preventing accidents. A feature of the AI is the live alert system that sends text messages or emails to a user defined destination. In a trespassing scenario, it is conceivable for the AI to inform railroad staff that a trespasser is present along their property. At this point law enforcement could be contacted and a trespasser could be removed before potentially catastrophic consequences occur. (64)

At the second non-grade crossing location, the AI analyzed 48 hours of live footage between July 29th 2018 and July 30th 2018, successfully detecting 109 trespassing events. This live stream overlooks a stretch of track leading to a grade crossing that can be seen at the far upper-right of the screen. The detection of grade crossing specific trespass events was impossible at this location due to an obstructed view of the active signalization and extreme distance of crossing in the frame. Despite these limitations a non-grade crossing region of interest was identified, and trespassing events were detected. Table 7 shows a summary of the trespassing events witnessed during the testing period of the second study.

Table 7 Summary of Trespassing Events during Second Non-Grade Crossing Study

				Violations		
Date	From	To	Duration (Hours)	Car	Pedestrian	Truck
7/29/2018	0:00	23:59	24:00:00	0	49	0
7/30/2018	0:00	23:59	24:00:00	0	60	0
		Total Time	48:00:00	0	109	0
		Total	109	0.00%	100.00%	0.00%

A full listing of the trespassing events and corresponding video files can be seen in Table 10 Appendix – Framework 2 Second Non-Grade Crossing Study Results with

Reference Video. Compared to the first testing location there were many trespassing events witnessed during the study period. Some of these events can be seen in Figure 17.

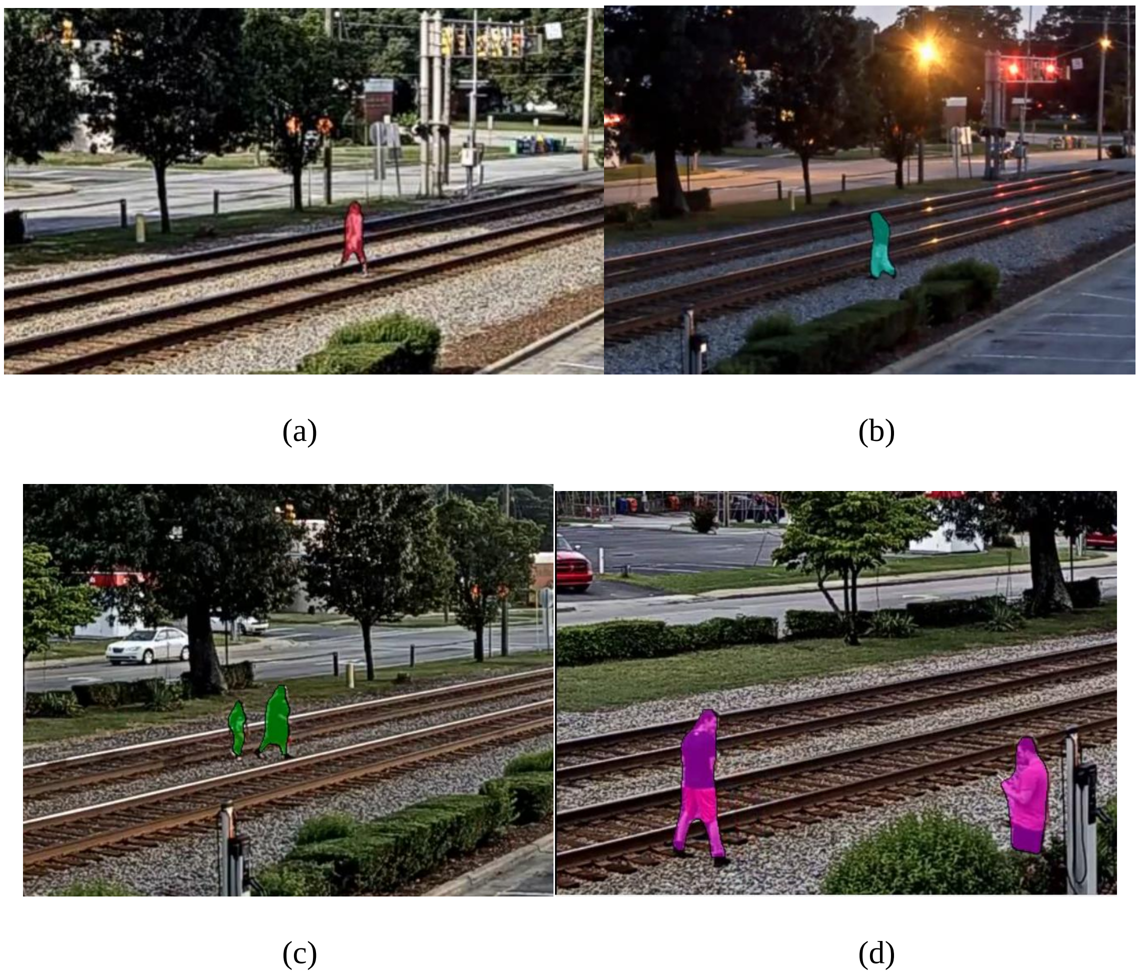


Figure 17 (a) Trespasser Crossing Tracks from Parking Lot to Downtown Area (b) Trespassers Crossing in Evening Conditions (c) Adult and Child Trespassers Crossing Railroad Tracks (d) Two Trespassers Loitering on Tracks Near the Parking Lot Area

Some cases captured by the AI appear to show trespassers using the railroad property as a shortcut to travel between a parking lot to a downtown area. If, after aggregating this information into a larger trespassing database, this trend proves to be a common occurrence it is possible to develop solutions to this trespassing problem. For example, the installation of fencing along the railroad right of way or the construction of a dedicated walkway at the far grade crossing may deter trespassing on the railroad tracks here. Learning from trespass incidents have the potential to inform education, enforcement, and engineering solutions to the greatest safety problem faced by the railroad industry today.

3.4 Live Video Data Analysis Tool

The AI algorithm previously described will be integrated into a web-based video analytics tool that Rutgers University has developed. This tool streamlines the automatic analysis of live video data from various sources. The program can analyze live feeds through following steps;

- Step 1: Log in to the web-based application tool
- Step 2: Insert the URL for the railroad live stream
- Step 3: Select the region of interests (grade crossing and non-grade crossing)
- Step 4: (Grade Crossing Only) Click within the presented image of the stream selecting a visible crossing signal light
- Step 5: Enter either a phone number or email address destination for live alerts
- Step 6: Click submit and processing will begin
- Step 7: Trespassing events notifications with cropped trespass clips will be sent to the chosen destination and aggregated on a server for later analysis

3.5 Tool Performance

To ensure that the AI algorithm achieved maximum accuracy a several step validation plan was enacted. Four results of the analysis were possible; an illegal trespass occurs, and a detection is recorded (true positives), no illegal trespass occurs but a detection is recorded (false positive), a trespass occurs, and no detection is recorded (false negative), no trespass occurs, and no detection is recorded (true negative). In the training section, the AI analyzed 129 hours of live video data and reported a conglomeration of correct and incorrect trespassing identification as compared to ground truth data acquired by student's manual review of archival footage. These mistakes were corrected by improving the algorithm, and a recording of the live feed was re-processed with the updated algorithm to ensure that the false positives and false negatives would not occur again resulting in the algorithm achieving 100% accuracy at this point.

In the testing phase two non-grade crossing were analyzed with no intermittent program modifications. Over 100 live hours of combined non-grade crossing footage was manually reviewed and compared to the results generated by the algorithm. To date, the program was 100% accurate (no false negative or false positive). We are continuing to expand the amount of live video data analyzed to ensure the performance is consistent in all encounterable scenarios.

3.6 Contributions to Research and Practice

3.6.1 Contributions to Academic Research

This framework is the first use of Mask R-CNN algorithm for trespassing detection in the railroad industry. This AI provides a structure for automatically gathering information from railroad live feeds. Previously, collecting data on railroad trespassing required extensive manual labor. With the advent of this AI technology accumulating large data sets of trespassing for human factors research in trespassing is achievable.

3.6.2 Contributions to Practice

The practical contribution of this framework is the tool created to implement its functionality. Without requiring practitioners to program their own algorithms, our tool can analyze railroad feeds in real time to supplement human based surveillance. Manually reviewing the extensive CCTV network is laborious and can be made easier with the implementation of the framework described in this research. The framework can automatically gather trespasses to inform long term strategic education, enforcement and engineering solutions in the future. The live alert aspect of the tool can aid railroads in responding to potentially dangerous situations.

3.7 CONCLUSION

This chapter proposes the use of an Artificial Intelligence algorithm for the automatic detection of trespassing events that improves upon the first framework by addressing the limitations outlined by industry professional and peer feedback. The collected trespass data can help better understand trespassing behaviors and characteristics in support of developing informed risk mitigation strategies related to engineering, education or enforcement. The framework was implemented on three live streams within the United States, including one grade crossing and two non-grade crossing. During the study, our AI correctly detected all trespassing events at the selected locations and achieved an accuracy of 100% during the analyzed period. The live alerts generated in this research could be potentially used for a series of trespassing research activities in the future. This research indicates a promising application of AI to real-time video analytics for trespassing and potentially other challenges within the railroad industry.

Bibliography

1. Batory RL. As Prepared Remarks of Federal Railroad Administration. Vol. 12. Denver, CO; 2018.

2. FRA. Trespasser Casualties [Internet]. 2018. Available from: https://safetydata.fra.dot.gov/officeofsafety/publicsite/query/castally4.aspx

3. Federal Railroad Administration (FRA). Highway-Rail Grade Crossings Overview. In 2017. Available from: https://www.fra.dot.gov/Page/P0156

4. Railroad trespassing fatalities in the U.S. reach 10-year high. NBC News [Internet]. 2018. Available from: https://www.nbcnews.com/news/us-news/railroad-trespassing-fatalities-u-s-reach-10-year-high-n852881

5. U.S. House Committee on Appropriations. Departments of Transportation, and Housing and Urban Development and Related Agencies Appropriations Bill, 2018. US House of Representatives. 2017;50.

6. FRA. Table 1.12 - Ten Year Accident/Incident Overview [Internet]. 2017. Available from: https://safetydata.fra.dot.gov/OfficeofSafety/publicsite/Query/TenYearAccidentIncidentOverview.aspx

7. Gnoni MG, Saleh JH. Near-miss management systems and observability-in-depth: Handling safety incidents and accident precursors in light of safety principles. Safety Science. 2017;91:154–167.

8. Phimister JR, Oktem U, Kleindorfer PR, Kunruther and H. Near-Miss Incident Management in the Chemical Process Industry. Risk Analysis. 2003;23(3):445–459.

9. Federal Railroad Administration (FRA). Grade Crossing Safety Improvement Program. Federal Transit Administration (FTA), US Department of Transportation. 2016;

10. Metro Transit. F.R.A. Awards $5 Million to Improve Metro-North and Long Island Rail Road Crossings [Internet]. MTA.info. 2017. Available from: http://www.mta.info/news-metro-north-grade-crossings-fra/2016/09/12/fra-awarded-about-5m-improve-metro-north-and-long.

11. Sheyner G. Palo Alto to install cameras along Caltrain tracks. [Internet]. Palo Alto Online. 2018. Available from: https://www.paloaltoonline.com/news/2018/03/20/palo-alto-to-install-cameras-along-caltrain-tracks

12. Buget 2018: All 11,000 trains, 8,500 stations to have CCTV surveillance [Internet]. 2018. Available from: https://timesofindia.indiatimes.com/business/india-business/rail-budget-2018-all-11000-trains-8500-stations-to-have-cctv-surveillance/articleshow/62606244.cms

13. M. DH, Velastin SA. How Close Are We to Solving the Problem of Automated Visual Surveillance? In: Machine Vision & Application. 2008.

14. Dadashi N. Automatic Surveillance and CCTV Operator Workload. University of Nottingham. Nottingham: UK; 2008.

15. Ngamdung T, Driver and M daSilva. Behavior Analysis at Highway-Rail Grade Crossings using Field Operational Test Data—Light Vehicles. Joint Rail Conference American Society of Mechanical Engineers. 2012;

16. daSilva MP, Baron W, Carroll and AA. Highway Rail-Grade Crossing Safety Research: Railroad Infrastructure Trespassing Detection Systems Research in Pittsford. New York DOT-VNTSC-FRA-05-07 John A Volpe National Transportation Systems. 2012;

17. Pu Y, Chen L, Lee S. Study of Moving Obstacle Detection at Railway Crossing by Machine Vision. Information Technology Journal. 2014;13:2611–2618.

18. Zhang Z, Trivedi C, Liu X. Automated detection of grade-crossing-trespassing near misses based on computer viio analysis of surveillance video data. Safety Science [Internet]. 2017; Available from: https://doi.org/10.1016/j.ssci.2017.11.023

19. Zaman A, Liu X, Zhang Z. Video Analytics for Railroad Safety Research: An Artificial Intelligence Approach. Transportation Research Board. 2018;97.

20. Faghri A, Demetsky and MJ. Evaluation of Methods for Predicting Rail Highway Crossing Hazards. No; 1986.

21. Ogden BDR-H. Grade Crossing Handbook - Revised Second Edition 2007. Federal Highway Administration Office of Safety Design. Washington DC; 2007.

22. Caird JK. A Human Factors Analysis of Highway-Railway Grade Crossing Accidents in Canada. Transportation Development. 2002;

23. Chadwick SG, Zhou N, Saat and MR. Highway-Rail Grade Crossing Safety Challenges for Shared Operations of High-Speed. In: Passenger and Heavy Freight Rail in the US Safety Science. 2014. p. 128–137.

24. Dimitropoulos K, Grammalidis N, Simitopoulos D, Pavlidou N, Strintzis and M. Aircraft Detection and Tracking Using Intelligent Cameras. Image Processing, IEEE International Conference. 2005;

25. Patel HA, Thakore and DG. Moving Object Tracking Using Kalman Filter. International Journal of Computer Science and Mobile Computing. 2013;2(4):326–332.

26. Ismail KA. Application of computer vision techniques for automated road safety analysis and traffic data collection. British Columbia: University of British Columbia. Vancouver, Canada; 2010.

27. Kocamaz MK, Gong J, Pires and BR. Vision-Based Counting of Pedestrians and Cyclists. In: 2016 IEEE Winter Conference Applications of Computer Vision (WACV),. Lake Placid, NY; 2016.

28. Tene O an. JP. Big Data for All: Privacy and User Control in the Age of Analytics, 11 Northwest. Journal of Technology & Intellectual Property Pg. 2013;239.

29. Metcalf J, Keller EF, Boyd and D. Perspectives on Big Data, Ethics, and Society. Council for Big Data, Ethics, and Society. 2017.

30. Madden M, Rainie and L. Americans' Attitudes About Privacy, Security and Surveillance. Pew Research Center: Internet, Science & Tech. 2017.

31. Raul AC. The privacy, data protection and cybersecurity law review. Law Business Research Ltd. 2016;

32. Federal Trade Comission. Federal Trade Commission Protecting America's Consumers. Fair Information Practice Principles, Federal Trade Commission. In 2017. Available from: https://web.archive.org/web/20090331134113/http

33. Frome A, Cheung G, Abdulkader A, Zennaro M, Wu B, Bissacco A, et al. Large-scale privacy protection in Google Street View. In: IEEE 12th International Conference on Computer Vision. 2009. p. 2373–2380.

34. Aloysius N, Geetha M. A review on deep convolutional neural networks,. In 2017. p. 0588–0592.

35. Krizhevsky A, Sutskever I, Hinton G. ImageNet Classification with Deep convolutional Neural Networks. In: Advances in neural information processing systems Vol 25. 2012. p. 1097–1105.

36. Girshick R, Donahue J, Darrell T, Malik J. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. In: 2014 IEEE Conference on Computer Vision and Pattern Recognition [Internet]. Columbus, OH; 2014. p. 580–587. Available from: http://ieeexplore.ieee.org.proxy.libraries.rutgers.edu/stamp/stamp.jsp

37. Girshick R. Fast R-CNN. In: IEEE International Conference on Computer Vision. Santiago; 2015. p. 1440–1448.

38. Ren S, He K, Girshick R, Sun J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2017 Jun 1;39(6):1137–1149.

39. He K, Gkioxari G, Dollar P, Girshick R. Mask R-CNN. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2018;

40. Lin TY. COCO: Common Objects in Context. Computer Vision – ECCV. 2014. 740–755 p.

41. Fakhfakh N, Khoudour L, El-Koursi EM, Jacot J, Dufaux and AA. Video-Based Object Detection System for Improving Safety at Level Crossings. Open transportation journal, supplement on" safety at Level Crossings". 2010.

42. Brunetti A, Buongiorno D, Trotta GF, Bevilacqua V. Computer vision and deep learning techniques for pedestrian detection and tracking: A survey. Neurocomputing. 2018;300:17–33.

43. Ghosh S, Amon P, Hutter A, Kaup A. Reliable pedestrian detection using a deep neural network trained on pedestrian counts. In: 2017 IEEE International Conference on Image Processing (ICIP), Beijing. 2017. p. 685–689.

44. Hou YL, Song Y, Hao X, Shen Y, Qian M. Multispectral pedestrian detection based on deep convolutional neural networks. In: 2017 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), Xiamen. 2017. p. 1–4.

45. John V, Mita S, Liu Z, Qi B. Pedestrian detection in thermal images using adaptive fuzzy C-means clustering and convolutional neural networks. In: 14th IAPR International Conference on Machine Vision Applications (MVA), Tokyo. 2015. p. 246–249.

46. Cao Y, Guan D, Huang W, Yang J, Cao Y, Qiao Y. Pedestrian detection with unsupervised multispectral feature learning using deep neural networks. Information Fusion Vol. 2019;46:206–217.

47. Liu J, Gao X, Bao N, Tang J, Wu G. Deep convolutional neural networks for pedestrian detection with skip pooling. In: 2017 International Joint Conference on Neural Networks (IJCNN). Anchorage, AK; 2017. p. 2056–2063.

48. Orozco CI, Berlles JJ, Buemi ME. New deep convolutional neural network architecture for pedestrian detection. In: 8th International Conference of Pattern Recognition Systems (ICPRS 2017). Madrid; 2017. p. 1–6.

49. Fukui H, Yamashita T, Yamauchi Y, and H. Murase HF. Pedestrian detection based on deep convolutional neural network with ensemble inference network,. In: IEEE Intelligent Vehicles Symposium (IV), Seoul. 2015. p. 223–228.

50. Tomè D, Monti F, Baroffio L, Bondi L, Tagliasacchi M, Tubaro S. Deep Convolutional Neural Networks for pedestrian detection. Signal Processing: Image Communication. Volume. 2016;47:482–489.

51. Zhang H, Du Y, Ning S, Zhang Y, Du C, Yang S. Pedestrian Detection Method Based on Faster R-CNN,. In: 2017 13th International Conference on Computational Intelligence and Security (CIS), Hong Kong. 2017. p. 427–430.

52. Budak Ü, Halici U, Şengür A. Deep convolutional neural networks for airport detection in remote sensing images,. In: 2018 26th Signal Processing and Communications Applications Conference (SIU), Izmir. 2018. p. 1–4.

53. Ngeno KJ. Research on Ship Classification using Faster Region Convolutional Neural Network for Port Security. Waseda University. Tokyo; 2017.

54. Zhang L, Yang F, and Y. J. Zhu YDZ. Road crack detection using deep convolutional neural network,. In: 2016 IEEE International Conference on Image Processing (ICIP). Phoenix, AZ; 2016. p. 3708–3712.

55. Gibert X, Chellappa R, Patel VM. "Deep Multitask Learning for Railway Track Inspection," in. IEEE Transactions on Intelligent Transportation Systems. 2017 Jan;18(1):153–164.

56. Shah M, Javed O, Shafique and K. Automated Visual Surveillance in Realistic Scenarios. IEEE Computer Society. 2007;14(1).

57. Sheikh YA. Visual Monitoring of Railroad Grade Crossing. In: Defense and Security. 2004. p. 654–660.

58. Cucchiara R, Grana C, Piccardi M, Prati and A. Detecting Moving Objects, Ghosts, and Shadows in Video Streams. Pattern Analysis and Machine Intelligence. 2003;25(10):1337–1342.

59. Salmane H, Khoudour L, Ruichek and Y. A Video-Analysis-Based Railway–Road Safety System for Detecting Hazard Situations at Level Crossings. IEEE Transactions on Intelligent Transportation Systems. 2015;(16):596–609.

60. Chen CH. Handbook of Pattern Recognition and Computer Vision. World Scientific; 2015.

61. FRA. Table 2-39: Railroad and Grade Crossing Fatalities by Victim Class. National Transportation Statistics [Internet]. 2017 Apr 16; Available from: https://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_statistics/html/table_02_39.html.

62. Saccomanno F, Fu LP, Miranda-Moreno and L. Risk-Based Model for Identifying Highway-Rail Grade Crossing Blackspots. Transportation Research Record: Journal of the Transportation Research Board. 2004;1862:127–135.

63. Valera M, Velastin and SA. Intelligent Distributed Surveillance Systems: A Review. In: IEE Proceedings-Vision, Image and Signal Processing. 2005. p. 192–204.

64. Foderaro F, Horton S. Law Enforcement Strategies for Preventing Rail Trespassing. US Department of Transportation John A Volpe National Transportation Systems Center. 2016;

65. Wang X, Liu J, Khattak AJ, Clarke D. Non-crossing rail-trespassing crashes in the past decade: A spatial approach to analyzing injury severity. Safety Science Volume. 2016 Jul;82:44–55.

66. Savage I. Trespassing on the Railroad. Research in Transportation Economics. 2007 Jul;20:199–224.

67. Herschel R, V.M M. Ethics & Big Data. Technology in Society. 2017;49:31–36.

68. Zook M, Barocas S, Boyd D, Crawford K, Keller E, Gangadharan SP. Ten simple rules for responsible big data research. PLoS Computational Biology [Internet]. 1005;13(3). Available from: https://doi.org/10.1371/journal.pcbi.1005399

Appendix

Table 8 Appendix – Framework 2 Grade Crossing Study Results with Reference Video

Date	Time	Batch	Original Video	Violation	Violator(s)
7/19/2018	19:24:48	7_19_1	video_data_0000000377.mp4	grade crossing	{'car': 1}
7/20/2018	9:35:38	7_20_1	video_data_0000000131.mp4	grade crossing	{'person': 1}
7/20/2018	9:30:35	7_20_1	video_data_0000000070.mp4	Trespassing	{'person': 2}
7/20/2018	9:34:15	7_20_1	video_data_0000000118.mp4	grade crossing	{'person': 1}
7/20/2018	9:36:10	7_20_1	video_data_0000000143.mp4	grade crossing	{'car': 2}
7/20/2018	9:36:20	7_20_1	video_data_0000000153.mp4	grade crossing	{'car': 1}
7/20/2018	10:06:00	7_20_1	video_data_0000000502.mp4	grade crossing	{'car': 1}
7/20/2018	10:06:30	7_20_1	video_data_0000000509.mp4	grade crossing	{'car': 1}
7/20/2018	10:11:10	7_20_1	video_data_0000000557.mp4	grade crossing	{'car': 2}
7/20/2018	10:11:20	7_20_1	video_data_0000000562.mp4	grade crossing	{'car': 1}
7/20/2018	10:11:15	7_20_1	video_data_0000000569.mp4	Trespassing	{'person': 1}
7/20/2018	10:35:30	7_20_1	video_data_0000000850.mp4	Trespassing	{'person': 1}
7/20/2018	11:15:20	7_20_1	video_data_0000001332.mp4	grade crossing	{'car': 1}
7/20/2018	11:15:40	7_20_1	video_data_0000001339.mp4	grade crossing	{'car': 1}
7/20/2018	11:16:50	7_20_1	video_data_0000001351.mp4	grade crossing	{'car': 1}
7/20/2018	11:20:55	7_20_1	video_data_0000001390.mp4	grade crossing	{'car': 1}
7/20/2018	11:21:30	7_20_1	video_data_0000001410.mp4	grade crossing	{'car': 1}
7/20/2018	11:36:10	7_20_1	video_data_0000001583.mp4	grade crossing	{'car': 1}
7/20/2018	11:38:45	7_20_1	video_data_0000001613.mp4	grade crossing	{'car': 2}
7/20/2018	11:38:55	7_20_1	video_data_0000001624.mp4	grade crossing	{'car': 1}

Date	Time	Batch	Original Video	Violation	Violator(s)
7/20/2018	11:51:30	7_20_1	video_data_0000001769.mp4	grade crossing	{'car': 1}
7/20/2018	11:52:10	7_20_1	video_data_0000001776.mp4	grade crossing	{'truck': 1, 'car': 1}
7/20/2018	1:11:23	7_20_2	video_data_0000000003.mp4	grade crossing	{'car': 1}
7/20/2018	1:11:23	7_20_2	video_data_0000000004.mp4	grade crossing	{'car': 1}
7/20/2018	1:11:23	7_20_2	video_data_0000000005.mp4	grade crossing	{'car': 1}
7/20/2018	1:11:23	7_20_2	video_data_0000000006.mp4	grade crossing	{'car': 1}
7/20/2018	1:11:23	7_20_2	video_data_0000000005.mp4	grade crossing	{'truck': 1}
7/20/2018	1:11:23	7_20_2	video_data_0000000006.mp4	grade crossing	{'car': 1}
7/20/2018	16:35:44	7_20_3	video_data_0000000061.mp4	grade crossing	{'car': 2}
7/20/2018	17:00:36	7_20_3	video_data_0000000360.mp4	grade crossing	{'car': 2}
7/20/2018	17:09:47	7_20_3	video_data_0000000362.mp4	grade crossing	{'car': 2}
7/20/2018	17:22:34	7_20_3	video_data_0000000623.mp4	grade crossing	{'car': 1}
7/20/2018	17:31:42	7_20_3	video_data_0000000733.mp4	grade crossing	{'car': 1}
7/20/2018	17:34:12	7_20_3	video_data_0000000763.mp4	grade crossing	{'car': 2}
7/20/2018	17:59:05	7_20_3	video_data_0000001062.mp4	grade crossing	{'car': 1}
7/21/2018	4:31:22	7_21_1	video_data_0000002495.mp4	grade crossing	{'car': 1}
7/21/2018	4:31:26	7_21_1	video_data_0000002497.mp4	grade crossing	{'car': 1}
7/21/2018	5:37:17	7_21_1	video_data_0000003292.mp4	grade crossing	{'car': 1}
7/21/2018	5:37:20	7_21_1	video_data_0000003321.mp4	grade crossing	{'car': 1}
7/21/2018	8:37:44	7_21_3	video_data_0000000177.mp4	Trespassing	{'person': 1}
7/21/2018	8:37:51	7_21_3	video_data_0000000181.mp4	grade crossing	{'person': 1}
7/21/2018	8:39:59	7_21_3	video_data_0000000209.mp4	grade crossing	{'car': 1}

Date	Time	Batch	Original Video	Violation	Violator(s)
7/21/2018	8:40:04	7_21_3	video_data_0000000217.mp4	grade crossing	{'car': 2}
7/21/2018	8:40:05	7_21_3	video_data_0000000219.mp4	grade crossing	{'car': 1}
7/21/2018	9:01:41	7_21_3	video_data_0000000463.mp4	grade crossing	{'car': 1}
7/21/2018	9:01:42	7_21_3	video_data_0000000468.mp4	grade crossing	{'car': 1}
7/21/2018	9:05:44	7_21_3	video_data_0000000511.mp4	grade crossing	{'car': 2}
7/21/2018	9:05:46	7_21_3	video_data_0000000518.mp4	grade crossing	{'car': 2}
7/21/2018	9:37:37	7_21_3	video_data_0000000769.mp4	grade crossing	{'truck': 1, 'car': 1}
7/21/2018	9:37:45	7_21_3	video_data_0000000771.mp4	grade crossing	{'car': 2}
7/21/2018	9:37:44	7_21_3	video_data_0000000774.mp4	grade crossing	{'car': 2}
7/21/2018	10:31:36	7_21_3	video_data_0000001205.mp4	grade crossing	{'car': 1}
7/21/2018	10:31:40	7_21_3	video_data_0000001208.mp4	grade crossing	{'car': 2}
7/21/2018	10:31:43	7_21_3	video_data_0000001211.mp4	grade crossing	{'car': 2}
7/21/2018	11:21:27	7_21_3	video_data_0000001729.mp4	grade crossing	{'car': 1}
7/21/2018	11:21:30	7_21_3	video_data_0000001732.mp4	grade crossing	{'car': 2}
7/21/2018	11:39:46	7_21_3	video_data_0000002231.mp4	grade crossing	{'car': 1}
7/21/2018	11:39:48	7_21_3	video_data_0000002236.mp4	grade crossing	{'car': 2}
7/21/2018	14:17:53	7_21_4	video_data_0000000256.mp4	grade crossing	{'car': 2}
7/21/2018	14:18:50	7_21_4	video_data_0000000271.mp4	grade crossing	{'car': 2}
7/21/2018	14:28:20	7_21_4	video_data_0000000384.mp4	grade crossing	{'car': 1}
7/21/2018	14:29:08	7_21_4	video_data_0000000399.mp4	grade crossing	{'truck': 1, 'car': 2}
7/21/2018	14:29:10	7_21_4	video_data_0000000402.mp4	grade crossing	{'car': 2}
7/21/2018	18:12:30	7_21_7	video_data_0000000464.mp4	grade crossing	{'car': 1}

Date	Time	Batch	Original Video	Violation	Violator(s)
7/21/2018	19:22:40	7_21_7	video_data_0000001308.mp4	grade crossing	{'person': 3}
7/21/2018	19:22:47	7_21_7	video_data_0000001313.mp4	Trespassing	{'person': 1}
7/21/2018	19:24:00	7_21_7	video_data_0000001337.mp4	grade crossing	{'car': 2}
7/21/2018	21:13:00	7_21_9	video_data_0000000301.mp4	grade crossing	{'car': 1}
7/22/2018	10:26:42	7_22_1	video_data_0000000299.mp4	grade crossing	{'car': 2}
7/22/2018	10:26:44	7_22_1	video_data_0000000299.mp4	grade crossing	{'car': 2}
7/22/2018	10:45:27	7_22_1	video_data_0000000695.mp4	grade crossing	{'car': 1}
7/22/2018	10:45:30	7_22_1	video_data_0000000696.mp4	grade crossing	{'car': 2}
7/22/2018	10:57:00	7_22_1	video_data_0000000933.mp4	grade crossing	{'car': 1}
7/22/2018	11:41:50	7_22_2	video_data_0000000121.mp4	grade crossing	{'car': 2}
7/22/2018	12:30:22	7_22_2	video_data_0000000714.mp4	grade crossing	{'car': 3}
7/22/2018	13:02:43	7_22_2	video_data_0000001016.mp4	Trespassing	{'person': 1}
7/22/2018	13:10:16	7_22_2	video_data_0000001195.mp4	grade crossing	{'car': 2}
7/22/2018	13:10:15	7_22_2	video_data_0000001198.mp4	grade crossing	{'car': 1}
7/22/2018	13:14:30	7_22_2	video_data_0000001241.mp4	grade crossing	{'car': 1}
7/22/2018	13:14:32	7_22_2	video_data_0000001245.mp4	grade crossing	{'car': 1}
7/22/2018	13:53:39	7_22_4	video_data_0000000152.mp4	grade crossing	{'car': 1}
7/22/2018	13:53:44	7_22_4	video_data_0000000153.mp4	grade crossing	{'car': 2}
7/22/2018	14:03:13	7_22_4	video_data_0000000267.mp4	grade crossing	{'car': 2}
7/22/2018	14:42:48	7_22_4	video_data_0000000742.mp4	grade crossing	{'car': 2}
7/22/2018	15:03:31	7_22_4	video_data_0000000990.mp4	grade crossing	{'car': 1}
7/22/2018	15:08:21	7_22_4	video_data_0000001045.mp4	grade crossing	{'car': 1}

Date	Time	Batch	Original Video	Violation	Violator(s)
7/22/2018	15:08:28	7_22_4	video_data_0000001047.mp4	grade crossing	{'car': 1}
7/22/2018	15:31:18	7_22_4	video_data_0000001324.mp4	grade crossing	{'car': 1}
7/22/2018	16:50:58	7_22_5	video_data_0000000721.mp4	grade crossing	{'car': 3}
7/22/2018	16:53:14	7_22_5	video_data_0000000749.mp4	grade crossing	{'car': 1}
7/22/2018	17:07:09	7_22_5	video_data_0000000915.mp4	grade crossing	{'car': 1}
7/22/2018	17:13:04	7_22_5	video_data_0000000986.mp4	grade crossing	{'car': 1}
7/22/2018	17:37:48	7_22_5	video_data_0000001279.mp4	grade crossing	{'car': 1}
7/22/2018	17:57:35	7_22_5	video_data_0000001520.mp4	grade crossing	{'car': 1}
7/22/2018	18:06:28	7_22_5	video_data_0000001628.mp4	grade crossing	{'car': 1}
7/22/2018	18:09:59	7_22_5	video_data_0000001670.mp4	grade crossing	{'car': 1}
7/22/2018	18:10:02	7_22_5	video_data_0000001670.mp4	grade crossing	{'car': 1}
7/22/2018	19:14:28	7_22_5	video_data_0000002443.mp4	grade crossing	{'person': 2}
7/22/2018	19:14:37	7_22_5	video_data_0000002444.mp4	grade crossing	{'person': 2}
7/22/2018	21:33:07	7_22_5	video_data_0000002163.mp4	grade crossing	{'car': 1}
7/23/2018	3:15:18	7_23_1	video_data_0000001755.mp4	grade crossing	{'car': 1}
7/23/2018	3:49:13	7_23_1	video_data_0000002163.mp4	grade crossing	{'car': 1}
7/23/2018	10:45:37	7_23_2	video_data_0000000702.mp4	grade crossing	{'car': 1}
7/23/2018	10:45:50	7_23_2	video_data_0000000706.mp4	grade crossing	{'car': 1}
7/23/2018	11:15:34	7_23_2	video_data_0000001055.mp4	grade crossing	{'car': 1}
7/23/2018	15:50:45	7_23_5	video_data_0000000025.mp4	grade crossing	{'car': 1}
7/23/2018	16:37:40	7_23_5	video_data_0000000589.mp4	Trespassing	{'person': 1}
7/23/2018	16:38:20	7_23_5	video_data_0000000601.mp4	Trespassing	{'person': 1}

Date	Time	Batch	Original Video	Violation	Violator(s)
7/23/2018	16:52:33	7_23_5	video_data_0000000770.mp4	grade crossing	{'car': 1}
7/23/2018	17:05:18	7_23_5	video_data_0000000925.mp4	Trespassing	{'person': 1}
7/23/2018	17:05:28	7_23_5	video_data_0000000935.mp4	Trespassing	{'person': 1}
7/23/2018	17:45:30	7_23_6	video_data_0000000023.mp4	Trespassing	{'person': 1}
7/23/2018	18:06:14	7_23_7	video_data_0000000275.mp4	grade crossing	{'car': 1}
7/23/2018	18:24:26	7_23_7	video_data_0000000491.mp4	grade crossing	{'car': 1}
7/23/2018	22:45:31	7_23_7	video_data_0000003623.mp4	grade crossing	{'car': 1}
7/24/2018	3:10:50	7_24_1	video_data_0000002186.mp4	grade crossing	{'car': 1}
7/24/2018	4:33:53	7_24_1	video_data_0000003184.mp4	grade crossing	{'car': 1}
7/24/2018	11:48:56	7_24_2	video_data_0000000317.mp4	grade crossing	{'car': 1}
7/24/2018	12:12:52	7_24_2	video_data_0000000627.mp4	grade crossing	{'person': 2}
7/24/2018	12:14:23	7_24_2	video_data_0000000646.mp4	grade crossing	{'car': 3}
7/24/2018	12:35:41	7_24_2	video_data_0000000890.mp4	Trespassing	{'person': 1}
7/24/2018	13:31:17	7_24_2	video_data_0000001576.mp4	grade crossing	{'car': 1}
7/24/2018	13:32:06	7_24_2	video_data_0000001586.mp4	grade crossing	{'car': 1}
7/24/2018	16:42:28	7_24_2	video_data_0000003869.mp4	grade crossing	{'car': 1}
7/25/2018	12:48:27	7_25_2	video_data_0000001516.mp4	Trespassing	{'person': 2}
7/25/2018	12:48:31	7_25_2	video_data_0000001517.mp4	Trespassing	{'person': 2}
7/25/2018	13:02:16	7_25_2	video_data_0000001685.mp4	grade crossing	{'car': 2}
7/25/2018	13:24:13	7_25_2	video_data_0000001949.mp4	grade crossing	{'car': 1}
7/25/2018	13:58:05	7_25_2	video_data_0000002352.mp4	Trespassing	{'person': 1}
7/25/2018	14:08:20	7_25_2	video_data_0000002479.mp4	grade crossing	{'bus': 1}

Date	Time	Batch	Original Video	Violation	Violator(s)
7/25/2018	14:11:56	7_25_2	video_data_0000002520.mp4	grade crossing	{'car': 2}
7/25/2018	21:24:59	7_25_3	video_data_0000000436.mp4	grade crossing	{'car': 1}

Table 9 Appendix – Framework 2 First Non-Grade Crossing Study Results with Reference Video

Date & Time	Video File name	Violation	Violator(s)
7/22/2018 10:04	video_data_0000000115.mp4	Trespassing	{'person': 1}
7/23/2018 13:29	video_data_0000000238.mp4	Trespassing	{'person': 1}
7/23/2018 21:13	video_data_0000002772.mp4	Trespassing	{'person': 1}
7/23/2018 21:17	video_data_0000002865.mp4	Trespassing	{'person': 3}
7/24/2018 5:32	video_data_0000003965.mp4	Trespassing	{'person': 1}
7/24/2018 6:19	video_data_0000000227.mp4	Trespassing	{'person': 1}
7/25/2018 14:49	video_data_0000002938.mp4	Trespassing	{'person': 1}

Table 10 Appendix – Framework 2 Second Non-Grade Crossing Study Results with Reference Video

Time	Original Video	Violation	Violator(s)
7/29/2018 9:42	video_data_0000002067.mp4	Trespassing	{'person': 1}
7/29/2018 9:42	video_data_0000002069.mp4	Trespassing	{'person': 1}
7/29/2018 9:42	video_data_0000002069.mp4	Trespassing	{'person': 1}
7/29/2018 9:46	video_data_0000002161.mp4	Trespassing	{'person': 1}
7/29/2018 9:46	video_data_0000002161.mp4	Trespassing	{'person': 1}
7/29/2018 10:09	video_data_0000002648.mp4	Trespassing	{'person': 1}
7/29/2018 10:10	video_data_0000002649.mp4	Trespassing	{'person': 1}
7/29/2018 10:21	video_data_0000002871.mp4	Trespassing	{'person': 1}
7/29/2018 10:21	video_data_0000002872.mp4	Trespassing	{'person': 1}
7/29/2018 10:29	video_data_0000003033.mp4	Trespassing	{'person': 1}
7/29/2018 10:29	video_data_0000003034.mp4	Trespassing	{'person': 1}
7/29/2018 10:29	video_data_0000003036.mp4	Trespassing	{'person': 2}
7/29/2018 10:29	video_data_0000003038.mp4	Trespassing	{'person': 2}
7/29/2018 10:29	video_data_0000003039.mp4	Trespassing	{'person': 2}
7/29/2018 13:15	video_data_0000000284.mp4	Trespassing	{'person': 1}
7/29/2018 13:15	video_data_0000000285.mp4	Trespassing	{'person': 1}
7/29/2018 13:18	video_data_0000000316.mp4	Trespassing	{'person': 1}

Time	Original Video	Violation	Violator(s)
7/29/2018 13:18	video_data_0000000316.mp4	Trespassing	{'person': 1}
7/29/2018 13:18	video_data_0000000317.mp4	Trespassing	{'person': 1}
7/29/2018 13:18	video_data_0000000317.mp4	Trespassing	{'person': 1}
7/29/2018 13:18	video_data_0000000317.mp4	Trespassing	{'person': 1}
7/29/2018 15:05	video_data_0000001608.mp4	Trespassing	{'person': 1}
7/29/2018 15:05	video_data_0000001609.mp4	Trespassing	{'person': 1}
7/29/2018 15:07	video_data_0000001633.mp4	Trespassing	{'person': 1}
7/29/2018 15:07	video_data_0000001633.mp4	Trespassing	{'person': 1}
7/29/2018 15:07	video_data_0000001634.mp4	Trespassing	{'person': 1}
7/29/2018 15:14	video_data_0000001718.mp4	Trespassing	{'person': 1}
7/29/2018 15:14	video_data_0000001718.mp4	Trespassing	{'person': 1}
7/29/2018 15:14	video_data_0000001718.mp4	Trespassing	{'person': 1}
7/29/2018 15:19	video_data_0000001776.mp4	Trespassing	{'person': 1}
7/29/2018 15:19	video_data_0000001777.mp4	Trespassing	{'person': 1}
7/29/2018 15:19	video_data_0000001778.mp4	Trespassing	{'person': 1}
7/29/2018 15:28	video_data_0000001880.mp4	Trespassing	{'person': 1}
7/29/2018 15:28	video_data_0000001881.mp4	Trespassing	{'person': 1}
7/29/2018 15:28	video_data_0000001882.mp4	Trespassing	{'person': 1}
7/29/2018 15:51	video_data_0000002152.mp4	Trespassing	{'person': 1}
7/29/2018 15:57	video_data_0000002224.mp4	Trespassing	{'person': 1}
7/29/2018 15:57	video_data_0000002225.mp4	Trespassing	{'person': 1}
7/29/2018 15:57	video_data_0000002225.mp4	Trespassing	{'person': 1}
7/29/2018 15:57	video_data_0000002225.mp4	Trespassing	{'person': 1}
7/29/2018 17:33	video_data_0000003375.mp4	Trespassing	{'person': 1}
7/29/2018 18:42	video_data_0000004205.mp4	Trespassing	{'person': 1}
7/29/2018 18:42	video_data_0000004206.mp4	Trespassing	{'person': 1}
7/29/2018 18:42	video_data_0000004207.mp4	Trespassing	{'person': 1}
7/29/2018 18:42	video_data_0000004207.mp4	Trespassing	{'person': 1}
7/29/2018 18:47	video_data_0000004271.mp4	Trespassing	{'person': 1}
7/29/2018 19:25	video_data_0000000366.mp4	Trespassing	{'person': 2}
7/29/2018 19:28	video_data_0000000404.mp4	Trespassing	{'person': 1}
7/29/2018 19:29	video_data_0000000406.mp4	Trespassing	{'person': 2}
7/30/2018 8:29	video_data_0000001436.mp4	Trespassing	{'person': 1}
7/30/2018 8:29	video_data_0000001437.mp4	Trespassing	{'person': 1}
7/30/2018 8:38	video_data_0000001545.mp4	Trespassing	{'person': 1}
7/30/2018 8:41	video_data_0000001583.mp4	Trespassing	{'person': 1}
7/30/2018 8:43	video_data_0000001607.mp4	Trespassing	{'person': 1}
7/30/2018 8:52	video_data_0000001712.mp4	Trespassing	{'person': 1}
7/30/2018 8:52	video_data_0000001713.mp4	Trespassing	{'person': 1}
7/30/2018 10:04	video_data_0000002578.mp4	Trespassing	{'person': 2}

Time	Original Video	Violation	Violator(s)
7/30/2018 10:04	video_data_0000002578.mp4	Trespassing	{'person': 1}
7/30/2018 10:06	video_data_0000002602.mp4	Trespassing	{'person': 1}
7/30/2018 10:07	video_data_0000002605.mp4	Trespassing	{'person': 2}
7/30/2018 10:12	video_data_0000002664.mp4	Trespassing	{'person': 2}
7/30/2018 10:25	video_data_0000002823.mp4	Trespassing	{'person': 1}
7/30/2018 10:25	video_data_0000002824.mp4	Trespassing	{'person': 1}
7/30/2018 10:25	video_data_0000002825.mp4	Trespassing	{'person': 2}
7/30/2018 10:53	video_data_0000003163.mp4	Trespassing	{'person': 1}
7/30/2018 10:53	video_data_0000003163.mp4	Trespassing	{'person': 1}
7/30/2018 10:53	video_data_0000003164.mp4	Trespassing	{'person': 1}
7/30/2018 10:53	video_data_0000003165.mp4	Trespassing	{'person': 1}
7/30/2018 10:53	video_data_0000003166.mp4	Trespassing	{'person': 1}
7/30/2018 11:09	video_data_0000003354.mp4	Trespassing	{'person': 1}
7/30/2018 11:09	video_data_0000003355.mp4	Trespassing	{'person': 1}
7/30/2018 11:09	video_data_0000003358.mp4	Trespassing	{'person': 1}
7/30/2018 11:19	video_data_0000003472.mp4	Trespassing	{'person': 2}
7/30/2018 11:19	video_data_0000003473.mp4	Trespassing	{'person': 3}
7/30/2018 14:54	video_data_0000000150.mp4	Trespassing	{'person': 1}
7/30/2018 15:16	video_data_0000000414.mp4	Trespassing	{'person': 2}
7/30/2018 15:16	video_data_0000000415.mp4	Trespassing	{'person': 2}
7/30/2018 15:20	video_data_0000000461.mp4	Trespassing	{'person': 2}
7/30/2018 15:20	video_data_0000000462.mp4	Trespassing	{'person': 1}
7/30/2018 15:36	video_data_0000000642.mp4	Trespassing	{'person': 1}
7/30/2018 15:39	video_data_0000000686.mp4	Trespassing	{'person': 1}
7/30/2018 16:05	video_data_0000000996.mp4	Trespassing	{'person': 1}
7/30/2018 16:19	video_data_0000001169.mp4	Trespassing	{'person': 1}
7/30/2018 16:21	video_data_0000001187.mp4	Trespassing	{'person': 1}
7/30/2018 16:21	video_data_0000001188.mp4	Trespassing	{'person': 1}
7/30/2018 16:42	video_data_0000001448.mp4	Trespassing	{'person': 1}
7/30/2018 17:09	video_data_0000001763.mp4	Trespassing	{'person': 1}
7/30/2018 17:09	video_data_0000001764.mp4	Trespassing	{'person': 1}
7/30/2018 17:09	video_data_0000001764.mp4	Trespassing	{'person': 1}
7/30/2018 17:24	video_data_0000001944.mp4	Trespassing	{'person': 1}
7/30/2018 17:29	video_data_0000002007.mp4	Trespassing	{'person': 1}
7/30/2018 17:31	video_data_0000002032.mp4	Trespassing	{'person': 1}
7/30/2018 17:31	video_data_0000002033.mp4	Trespassing	{'person': 1}
7/30/2018 17:31	video_data_0000002034.mp4	Trespassing	{'person': 1}
7/30/2018 17:59	video_data_0000002372.mp4	Trespassing	{'person': 2}
7/30/2018 18:03	video_data_0000002411.mp4	Trespassing	{'person': 3}
7/30/2018 19:24	video_data_0000003392.mp4	Trespassing	{'person': 2}

Time	Original Video	Violation	Violator(s)
7/30/2018 20:28	video_data_0000004158.mp4	Trespassing	{'person': 2}
7/30/2018 20:28	video_data_0000004159.mp4	Trespassing	{'person': 1}
7/30/2018 20:29	video_data_0000004162.mp4	Trespassing	{'person': 2}
7/30/2018 20:29	video_data_0000004163.mp4	Trespassing	{'person': 1}
7/30/2018 20:29	video_data_0000004164.mp4	Trespassing	{'person': 1}
7/30/2018 20:29	video_data_0000004166.mp4	Trespassing	{'person': 1}
7/30/2018 20:29	video_data_0000004168.mp4	Trespassing	{'person': 1}
7/30/2018 20:30	video_data_0000004174.mp4	Trespassing	{'person': 1}
7/30/2018 20:30	video_data_0000004177.mp4	Trespassing	{'person': 2}
7/30/2018 20:31	video_data_0000004186.mp4	Trespassing	{'person': 3}
7/30/2018 20:43	video_data_0000000102.mp4	Trespassing	{'person': 1}
7/30/2018 21:51	video_data_0000000916.mp4	Trespassing	{'person': 1}