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Artificial Intelligence-Aided Automated Detection of Railroad Trespassing

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Abstract

Trespassing is the leading cause of rail-related deaths and has been on the rise for the past 10 years. Detection of unsafe trespassing of railroad tracks is critical for understanding and preventing fatalities. Witnessing these events has become possible with the widespread deployment of large volumes of surveillance video data in the railroad industry. This potential source of information requires immense labor to monitor in real time. To address this challenge this paper describes an artificial intelligence (AI) framework for the automatic detection of trespassing events in real time. This framework was implemented on three railroad video live streams, a grade crossing and two right-of-ways, in the United States. The 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 yet. This paper and its subsequent studies aim to provide the railroad industry with state-of-the-art AI tools to harness the untapped potential of an existing closed-circuit television infrastructure through the real-time analysis of their data feeds. The data generated from these studies will potentially help researchers understand human factors in railroad safety research and give them a real-time edge on tackling the critical challenges of 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. In the period of 2009–2016, 95 percent of railroad deaths were caused by trespassing and grade crossing collisions. The figure for trespassing casualties from 2013 to 2016 is 16 percent higher than 2009 to 2012 (*2–4*). This issue is recognized as a major concern of safety within the U.S., 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*).

Most rail trespassing behavior does not result in injuries or fatalities. These trespass events are not typically recorded in FRA safety databases because no immediate harm occurs. Not all trespassing events cause damage, but they indicate certain behaviors that may lead to severe consequences if they occur repeatedly. Learning from these trespass events is critical to developing effective education, enforcement, and engineering strategies for the prevention of trespassing on railroad tracks (*6*).

The increase in availability of video data within the rail industry makes acquiring data on trespassing more viable. Closed-circuit television (CCTV) cameras can be found throughout railroads, observing yards, bridges, grade crossings, and stations. Deployment of CCTV camera systems continue to grow in the U.S. following the 2015 Fixing Americas Surface Transportation (FAST) Act that mandated the installation of cameras throughout passenger railroads for the promotion of safety objectives (*7*). For example, Caltrain, in Palo Alto, California has installed CCTV cameras at safety-critical grade crossings to actively monitor and prevent illegal incursions through an integrated alert system (*8*). This trend has also expanded globally; for example, India has an initiative to install cameras on over 11,000 trains and 8,500 stations throughout the country starting in 2018

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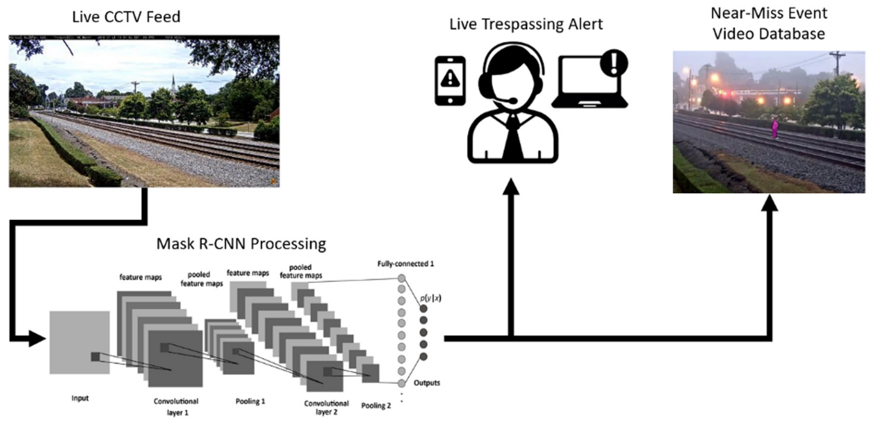

Figure 1. Conceptual trespasser detection & alert system using artificial intelligence.

(*9*). These sources provide valuable video big data resources for railroads, but analyzing the data accurately in real time is challenging.

At present, most camera systems are reviewed manually by railroad staff, but limited resources and operator fatigue (*10, 11*) can lead to potentially missing trespassing events. To address this challenge, this paper describes an artificial intelligence (AI) algorithm to "watch,""recognize," and "understand" trespassing events in real time using an existing video infrastructure. In addition, this algorithm is coupled to a live alert system that sends trespassing alerts to designated destinations. Once this technology is practice-ready, it can be adapted to new trespassing-critical locations to support railroad safety decisions.

Objectives of Research

The goal of this paper is to describe an AI framework which can analyze live video feeds in real time to gather useful information 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 trespassing data to understand trespassing characteristics

Figure 1 shows a conceptual view of the system, in which an AI algorithm can send live alerts to designated personnel by analyzing and identifying trespassing events in live CCTV feeds. In addition, trespassing events are also recorded in a trespass event database containing video and associated metadata (time of day, type of trespassing, type of trespasser, etc.).

Literature Review

A literature review was conducted to understand the state of the art and practice in two major categories: (1) how big video data are used within the railroad industry for trespassing detection; and (2) how AI is used for trespassing detection in other relevant domains.

Video Data and Trespassing in the Railroad

Trespassing on railroad property is primarily detected through manual observation of video surveillance systems. An example of this was research conducted by DaSilva et al. in which a video surveillance system was used to detect trespassers on railroad property in Pittsford, NY (*12*). In this study, a large amount of labor was required to review the footage and obtain true quantities for the number of trespasses. Minimal work has been done that utilizes 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.

Trespassing and illegal incursions at grade crossings make up much of the fatalities in the railroad industry (*2, 3*). Limited research has focused on the detection of the illegal incursions of grade crossings with AI solutions. Research by Pu et al. in 2014 used a series of computer vision algorithms to detect incursions with a facsimile of a grade crossing (*13*). Further research by Zhang et al. and Zaman et al. used a similar suite of AI algorithms to detect trespass events at grade crossings (*14, 15*). 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 right-of-ways can support railroads in two ways. The first is the potential for faster responses to dangerous situations on their property. Second, the aggregated database of these events can give insight into the behavioral characteristics of trespassers. This information has the potential to better understand trespassing and develop the most effective risk-mitigation strategies.

AI for Trespass Detection

AI has the potential to greatly reduce the required manpower to detect trespassers. Evidence of this exists within the utilization of AI algorithms in parallel industries such as highway and aviation. An emerging type of AI algorithm called Mask R-CNN has been successfully used in analyzing big video data in circumstances similar to the railroads trespassing problem.

Mask R-CNN is built on the established architecture of deep convolutional neural networks (DCNNs). DCNNs are a style of neural network that classifies images through a specific arrangement of three kinds of network layers: convolutional, rectified unit layers, 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 which is unique to what you want to classify. Multiple filters are tried across the entire image and are aggregated into a single image in the pooling layer. Rectified unit layers (ReLU) remove anything that does not match resulting in an image only showing what may match. If these steps are repeated in the algorithm, convolving, pooling, and convolving again, the algorithm becomes deep, resulting in a deep convolutional neural network (*16*).

Since Krizhevsky et al.'s 2012 research publication using DCNNs for image classification (*17*), which was used to win the ImageNet Large Scale Visual Recognition Challenge (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, for example Regional CNN (*18*), Fast R-CNN (*19*), and Faster R-CNN (*20*), 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 (*21*). 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 (*22*). These features of Mask R-CNN allow for rapid deployment of AI to object-recognition tasks.

In computer vision Mask R-CNN has several distinct advantages over other algorithms. It has 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 (*22*). Mask R-CNN is also invariant to changing environmental conditions in ways that traditional computer vision techniques, for example background subtraction (*13–15*) and blob analysis (*23*), 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 (*24*). These research initiatives have used convolutional neural networks to track people for a variety of purposes which closely mirror the needs of trespassing, for example autonomous driving (*25–27*), traffic safety (*28, 29*), and surveillance (*30–35*). 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 this research.

Many industries, including railroads, have used convolutional neural networks in other capacities. These applications range from airplane recognition in imagery (*36*) to the tracking of ships in ports (*37*) to roadway crack detection (*38*). Within the railroad industry, research by Gibert et al. used convolutional neural networks to identify missing track components in inspection photos (*39*).

Another commonly used computer vision technique is region of interest (ROI), which was used in a study to count pedestrians and cyclists crossing the frame of view of a CCTV camera. A user of the system can define a polygon of pixels within the frame, which AI algorithms can use for reference. Positive crossings were only recorded if identified pedestrians and cyclists passed through the ROI (*40*).

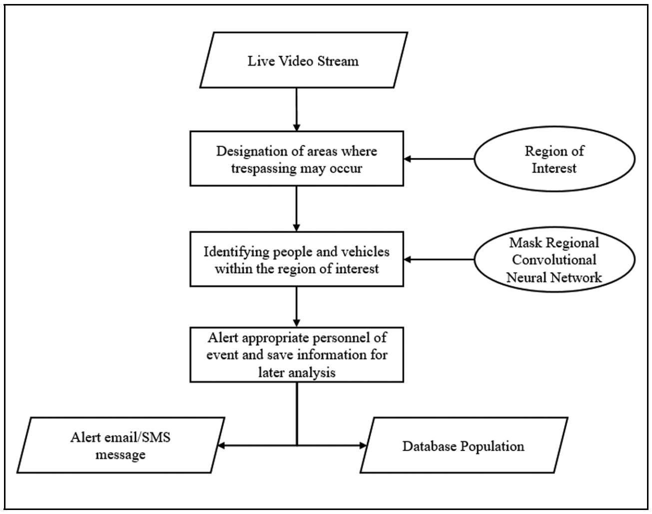

Figure 2. General AI framework for railroad trespass detection.

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 inform engineering, education, and enforcement strategies for trespass prevention.

AI-Aided Trespass Detection Framework

Detection of trespassing events in video feeds has many challenges. There are a wide variety of configurations, environmental variables, and technical features of live data streams watching 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, and fog). Finally, when analyzing a live video stream, the AI must be able to process the frames with enough speed to maintain a fast response time to possible trespassing events.

To address these challenges a generalized AI framework for trespass detection which utilizes the combined techniques of ROI (*40*) and Mask R-CNN (*21*) is proposed (Figure 2). 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 trespass data would be 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 (*22*). In addition, 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. First, 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. Second, a clip of the trespass incident is recorded and metadata, for example object detected, time, location, video file name, and so forth, are stored in a trespass event database. These metadata are automatically generated by the AI, demonstrating that context of the image can be extracted and interpreted. Trespass 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. In addition, 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 leads to the consideration of several concerns which will be addressed in the 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 and 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, and incorporate solutions into the AI.

Figure 3. (*a*) Selected grade crossing stream; (*b*) selected first right-of-way stream; (*c*) selected second right-of-way stream.

- 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.

Trespass Detection Applications

Most rail casualties result from trespassing in the form of grade crossing collisions and incursions on railroad right-of-ways (*2, 3*). Almost all prior studies in the field of trespassing and grade crossing safety have focused on the accident data (*41, 42*) without considering trespass events that do not result in accidents. These trespass events share similar behavior characteristics to accidents, with the exception that they do not result in immediate harm. Repeated trespass events 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 right-of-ways. Grade crossings are highway–rail intersections with active signalization where pedestrians and vehicles are alerted to an approaching train. Trespasses at grade crossings are defined as pedestrians and vehicles that enter the crossing after the signal lights are activated. Only pedestrians and vehicles who enter the ROI after the signal lights are active trigger trespassing alerts; therefore, the algorithm can differentiate between legal and illegal passes. Passive grade crossings, which lack active signalization like lights, arms, and gates, were not addressed in this study because of lack of available video coverage of these locations.

Right-of-way locations are defined as railroad property with no intersection or crossing and all incursions are deemed illegal, except for authorized railroad personnel. This categorization represents the two fundamentally different types of locations where trespassing occurs and was analyzed by the same generalized trespass detection framework.

In the 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 (*43*)

With these factors, three streams were identified for analysis. Figure 3 shows a typical view of the locations.

The selection of one grade crossing in Ashland, Virginia and two right-of-ways in Thomasville, North Carolina 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, the search for live video feeds will be expanded to examine a greater number of grade crossings and right-of-ways alike.

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

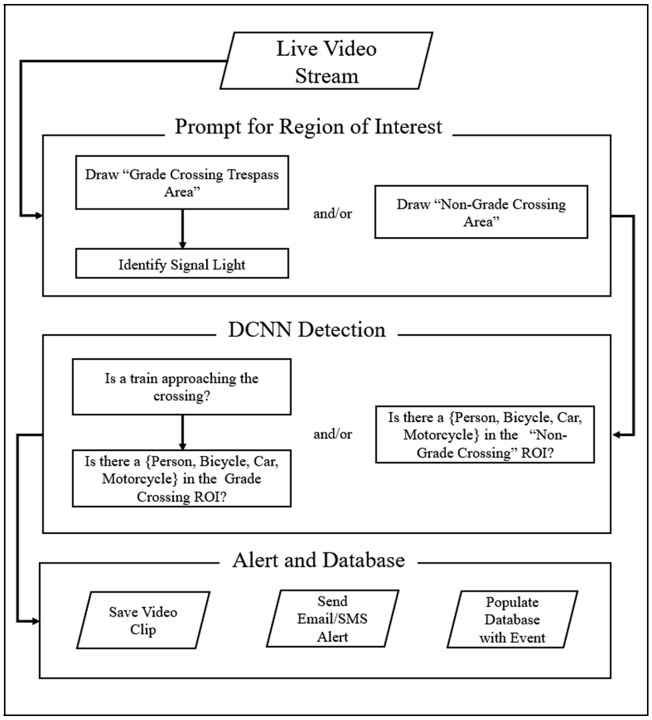

Figure 4. Detailed trespassing framework for railroad trespassing (including both grade crossing and right-of-way).

trespass has occurred. The detailed steps are presented below. The algorithm can analyze both grade crossings and right-of-ways 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. A diagram of this application framework can be seen in Figure 4.

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 are provided, for example via internet live stream, the program will proceed to step 2.

Step 2 Draw Region of Interest. 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 ROIs can be identified in the same frame and a differentiation between "right-of-way" 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 "right-of-way" 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. Several examples of region's of interest can be seen in Figure 5.

Step 3 Trespass Detection. The third step in the algorithm utilizes the Mask R-CNN framework (*21*). Each frame analyzed is checked for objects within the selected ROI. If a grade crossing ROI is identified a subroutine will actively check for the initiation of a crossing signal light. When that light activates, anyone who enters the ROI is deemed trespassing. Both freight and passenger trains are also identified by the algorithm but are deemed 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. Future research will 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

Figure 5. (*a*) ROI of grade crossing stream; (*b*) ROI of first right-of-way stream; (*c*) ROI of second right-of-way stream.

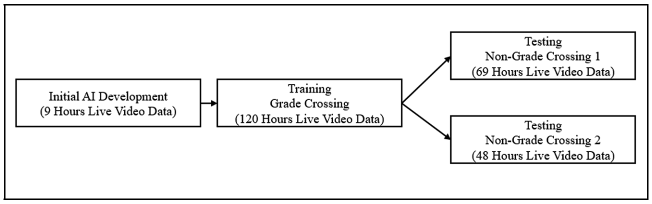

Figure 6. Algorithm development and testing flowchart.

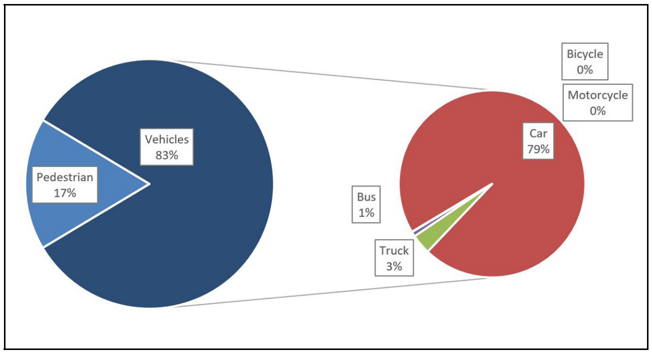

Figure 7. Distribution of grade crossing trespasser by type.

immediate action. The database contains information on time, object detection, identified zone (grade crossing vs. right-of-way) and name of the associated video file.

AI 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 put into place (Figure 6). The first step of this plan was the initial development of the AI using several hours of training data. These training data were acquired by recording the live stream of the selected grade crossing location for a duration of 9 h, capturing diverse environmental and traffic conditions. The research team established a known quantity of trespasses through manually inspecting the training data. The program then analyzed this footage and modifications were made to the program until 100% accuracy was achieved.

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 h analysis were identified, the AI was modified, and the archive was re-analyzed by the AI to ensure any problems had been resolved. False positives are the incorrect alert to a trespassing event when none occurred, and false negatives are missed trespasses which were not identified by the tool. Both errors were identified through meticulous manual reviewing of the raw video data. Changes to the AI were made and the video data were reprocessed ensuring that the errors were not repeated. The solutions to these issues ensured that that this error would not occur again in future scenarios with similar circumstances. The procedure followed by the team that identified false positives and missed detections is discussed later.

Tool Validation

The third and final step of this analysis was to test the AI on two new locations. Two right-of-ways were selected for this portion of the analysis and a cumulative 100 h of live video reviewed. These locations were selected because of 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.

Grade Crossing Results (Training)

During the 120 h of live footage of the grade crossing between 7/19/2018 and 7/25/2018, 140 positively identified trespassing events were 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 7 shows a breakdown of the results acquired during the analysis period. Six categories (Car, Truck, Bus, Person, Bicycle, Motorcycle) of trespassers were searched for by the AI algorithm. The ability of Mask R-CNN and supplied training data of the COCO dataset allowed for the identification of over 80 object categories (*21, 22*). Those selected for detection in the AI algorithm were Car, Truck, Bus, Person, Bicycle, and Motorcycle. This differentiation adds a dimension to the trespassing dataset and can inform sophisticated trespassing prevention solutions through detailed demographic analysis.

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. In total, 116 events of this kind were detected, making up 83% of all detected trespassing events at this location. Figure 8 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 privacy.

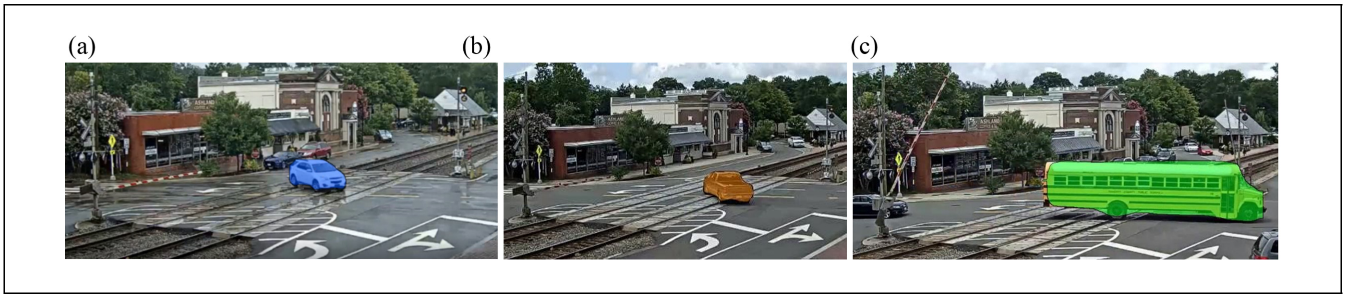

Figure 8. (*a*) Vehicle driving around deployed gates from far roadway; (*b*) vehicle driving around deployed gates from near roadway; (*c*) school bus crossing as gates are closing.

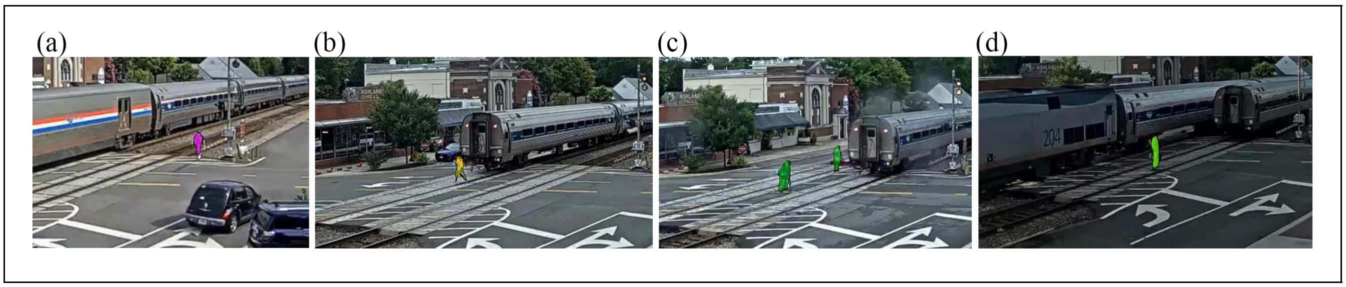

Figure 9. (*a*) Pedestrian walking behind gates; (*b*) pedestrian crossing behind train; (*c*) multiple pedestrians crossing behind train; (*d*) pedestrian waiting on railroad tracks.

The second most common trespassing events witnessed in this study were the illegal incursion of pedestrians while the active signalized gates were down. Some 24 events of this kind were detected, making up 17% of all totally detected trespassing events at this location. Figure 9 shows several typical detected examples of this. The color overlay of the individual represents a recognized object by the AI.

Both event types represent two typical nonconforming behaviors at grade crossings. The drivers and pedestrians who traverse the crossing while the gates are lowering have the confidence that they have enough time to pass the intersection before the train arrives. Individuals who crossed the intersection while the gates were rising 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 in trespass behavior can be understood. If data gathered by this AI indicate 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 (*44*). 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 (*44*). In the future, expansion of this research to more locations and the aggregation of a large trespass event database could highlight trends and inform solutions to the trespassing problem.

An additional feature of the Mask R-CNN (*21*) is its ability to automatically anonymize the trespasser. Within the United States privacy in big data is of paramount concern (*45, 46*). This is verified by surveys conducted in which 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" (*47*). The overlay of colored masks on detected trespassers prevents the identification of the individual. Similarly, masks over vehicles obscure the license plate sufficiently to prevent identification, therefore maintaining the privacy of the driver.

Right-of-Way 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 right-of-way location the AI analyzed 69 h of live footage between 7/21/2018 and 7/27/2018. During this time period, 10 trespassing events were recognized by the AI under several distinct environmental conditions, including rain, fog (Figure 10*a*), and nighttime

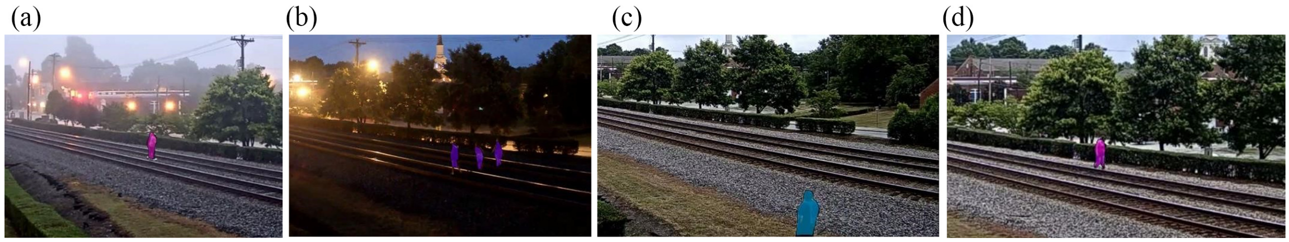

Figure 10. (*a*) Trespasser detected crossing in foggy weather; (*b*) group of trespassers detected at nighttime; (*c*) trespasser detected before crossing; (*d*) trespasser traveling within railroad property.

Figure 11. (*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.

(Figure 10*b*). During these times, the AI was able to correctly identify trespassers despite the sub-optimal detection conditions.

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 toward 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 (*44*).

At the second right-of-way location, the AI analyzed 48 h of live footage between 7/29/18 and 7/30/18, 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 trespasses was impossible at this location because of an obstructed view of the active signalization and extreme distance of crossing in the frame. Despite these limitations a right-of-way ROI was identified, and trespassing events were detected. Some of these events can be seen in Figure 11.

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 trespass event 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 events has the potential to inform education, enforcement, and engineering solutions to the most severe safety problem faced by the railroad industry today.

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 ROIs (grade crossing and right-of-way)
- 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 trespassing clips will be sent to the chosen destination and aggregated on a server for later analysis

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); and no trespass occurs, and no detection is recorded (true negative). In the training section, the AI analyzed 129 h of live video data and reported a conglomeration of correct and incorrect trespassing identification as compared with ground truth data acquired by manual review of archival footage. These mistakes were corrected by improving the algorithm, and a recording of the live feed was reprocessed 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 right-of-ways were analyzed with no intermittent program modifications. Over 100 live hours of combined right-of-way footage was manually reviewed and compared with the results generated by the algorithm. To date, the program was 100% accurate (no false negative or false positive). The research team is continuing to expand the amount of live video data analyzed to ensure the performance is consistent in all scenarios that might be encountered.

Contributions to Research and Practice

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 trespasses required extensive manual labor. With the advent of this AI technology, accumulating large datasets of trespassing events for human factors research in trespassing is achievable.

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, the 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 previously inaccessible data on trespassing to inform long-term strategic education, enforcement, and engineering solutions. If this practice-ready tool is implemented, the live alert function allows for immediate railroad response to potentially dangerous situations. Evaluation of this tool's effectiveness should be mapped through close examination of trespassing rates before and after implementation.

Conclusion

This paper proposes the use of an AI algorithm for the automatic detection of trespassing events. 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 algorithm was implemented on three live streams within the United States, including one grade crossing and two right-of-ways. During the study, the 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.

Future Work

To further validate this framework, the amount of data reviewed will be increased. This will allow the AI algorithm to experience more environmental conditions and possibly more trespassing events. A limitation of the current AI is the inability to differentiate between authorized personnel and trespassers. Future research will apply transfer learning techniques to update the AI's library to recognize authorized personnel through the identification of their personal protective equipment and other unique features. These techniques will also be used for future research into the recognition of debris and nonmoving objects on railroad tracks that may cause hazards for locomotives.

Once the AI has achieved an acceptable level of accuracy and can reliably recognize and alert to all relevant trespassing events, this application will be piloted with a railroad industry partner. In this partnership additional connections for the live alerts, such as audio warnings at the grade crossing or right-of-way locations, would be tested. Another future application may be using the developed AI algorithm to detect trespassing from front-facing cameras on the locomotives. In addition, future research will focus on utilizing the tool for countermeasure performance analysis. This will be accomplished by evaluation of behavioral trespass data before and after the implementation of trespass-prevention strategies. Future research is also planned to use these tools to understand the behavior of individuals in the pursuit of suicide prevention on railroad property.

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Author Contribution

The authors confirm contribution to the paper as follows: Study conception and design: AZ, BR, XL; Data collection, analysis and interpretation of results: AZ, BR, XL; Draft manuscript preparation: AZ, BR, XL. All authors reviewed the results and approved the final version of the manuscript.

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