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Video Analytics for Railroad Safety Research: An Artificial Intelligence Approach

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Abstract

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 human resources. To make the video analysis much less labor-intensive, this paper develops a framework for utilizing artificial intelligence (AI) technologies for the extraction of useful information from these big video datasets. This framework has been implemented based on the video data from one grade crossing in New Jersey. The AI algorithm can automatically detect unsafe trespassing of railroad tracks (called near-miss events in this paper). To date, the AI algorithm has analyzed hours of video data and correctly detected all near-misses. This pilot study indicates the promise of using AI for automated analysis of railroad video big data, thereby supporting data-driven railroad safety research. For practical use, our AI algorithm has been packaged into a computer-aided decision support tool (named AI-Grade) that outputs near-miss video clips based on user-provided raw video data. This paper 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 in order to better understand human factors in railroad safety research.

The availability of video data in the railroad industry is increasing every year. The 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 (*1*). The Los Angeles Metro Transit Authority in California began utilizing video cameras for law enforcement at grade crossings (*2*). In the New York area, Metro-North and the Long Island Rail Road received $5 million from the Federal Railroad Administration (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 (*3*). While video big data have been collected, analyzing these data quickly and reliably remains a challenge. In many cases, these camera systems are manually monitored by railroad staff, either live or subsequently reviewed in an archive.

There exist many scenarios in the rail industry where "near-misses"—or dangerous situations without actual incidents—occur. Because no actual harm occurs, these near-misses are typically not recorded in FRA safety databases. For example, if a pedestrian trespasses on a railroad track when the red signal is on, but this action does not result in an accident, we call it a near-miss. Although near-misses do not cause actual damage, they indicate certain characteristics that may ultimately cause severe consequences if they occur repeatedly. Learning from near-miss data is an important research topic in proactive risk management (*4*).

The pervasive presence of surveillance cameras provides a big data platform for collecting and analyzing near-miss 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. To address this technological challenge, this paper describes an artificial intelligence (AI)

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technology to let the computer program "watch," "identify," and "understand" near-miss clips automatically and efficiently utilizing an existing video infrastructure. Once this technology is practice-ready, it can be adapted to various applications in which video big data are used to support railroad safety decisions.

Objectives of Research

This paper aspires to develop an AI framework to gather useful information from video footage in support of railroad safety research. Specifically, this research aims to produce the following deliverables:

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

Literature Review

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

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 and daSilva (*5*) conducted a study to understand illegal trespassing on railroad property in Pittsford, New York. The video analysis required a large amount of human resources to accomplish (*6*). In addition, there have been studies on the effectiveness of humans watching CCTV cameras; they show that after 20–40 min of active monitoring, operators often suffer from "video blindness," which reduces their ability to effectively complete their task (*7*). Currently, there is minimal prior work on how AI can assist us in analyzing video big data, which is a principal knowledge gap that this research aims to fill. Effort has been made to quantify the frequency and severity of highway–rail grade crossing incidents. Previous studies (*8, 9*) employed the U.S. Department of Transportation (U.S. DOT) 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 (*10*). A comprehensive overview of grade crossing research was summarized by Chadwick et al. (*11*). Since grade crossing incidents account for a large portion of casualties on U.S. railroads (*11, 12*), it is important to better understand this type of risk so as to develop proper risk-mitigation strategies.

AI Technologies for Video Analytics

AI has the potential to tremendously reduce the laborious effort required to process video data. Similar sectors, such as roadways and airports, have begun to implement these techniques for video big data analysis. Selected AI techniques include background subtraction, region of interest, and Kalman filtering (*13–16*). 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 (*13*). Other techniques of video big data analysis, region of interest (ROI) and line of interest (LOI), were implemented in a study using a stationary CCTV camera to count pedestrians and cyclists crossing an intersection. 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 (*16*). Another AI technique is the Kalman filter, which is a set of mathematical equations to estimate the state of a process (*14*). This technique has been used to track vehicles within a camera view for highway applications (*15*).

While AI has the potential to provide useful data analysis capabilities, there are privacy concerns that may occur when collecting personally identifiable information (*17, 18*). For example, a survey showed that 88% of Americans "do not wish to have someone watch or listen to them without their permission" (*19*). A total of 63% of respondents "feel it is important to be able to go around in public without always being identified" (*19*). 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 U.S. citizens (*20*). 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 (*21*). 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 (*22*). In a full-scale implantation of video analysis on grade crossings, a similar anonymization algorithm could be implemented to preserve privacy.

Knowledge Gaps

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

Intended Contributions of this Paper

This paper 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 video big data in support of their safety decisions. Using an illustrative application in grade crossing near-miss detection using surveillance camera videos, we provide a step-by-step analytical procedure showing how AI can be developed and used to generate near-miss video clips. The methodology can be adapted to other scenarios toward automated, real-time, video monitoring and analysis. Near-miss data, which supplements accident data, provides additional useful information for understanding risky behaviors.

AI-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,

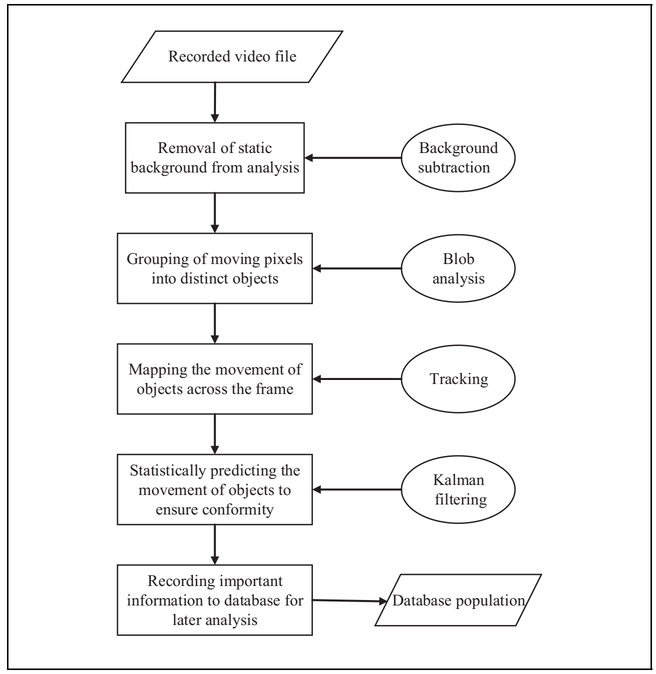

Figure 1. General AI framework for railroad video data analytics.

and when vehicles drive by headlights may cause a false detection. New opacity levels and extra checking techniques need be implemented to alleviate this issue.

To address the above-mentioned challenges, we introduce general AI approaches for video analytics, including background subtraction (*13, 23–25*), blob analysis (*26*), and Kalman filtering (*14, 16*, *27*, *28*) for potential application to railroad video analysis (Figure 1). 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 LOI or ROI, which aid in the counting and recording of objects' behavior as they traverse the frame. By isolating part of the frame, fewer pixel-to-pixel calculations are required, which is particularly useful in high-resolution footage where there are many pixels. 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 (*14*). 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.

The developed AI-based techniques should be trained to test and verify its robustness. A training program for an AI 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 (*13*). 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 is able to explicitly capture the images and moving paths of trains and highway users, such as cars, pedestrians, and cyclists, under a wide array of external conditions. Then the AI tool is able to record critical video information automatically, which is compiled into a database for future study.

Application to Grade Crossing Near-Miss Analysis

Grade crossing trespassing accounts for many incidents and fatalities annually (*29*). 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 near-misses. A near-miss 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 (*9, 30*), without accounting for a larger number of near-misses that share similar behavioral characteristics but (fortunately) did not cause any harm. The following section details the process of using AI to automatically detect near-misses from grade crossing video data. The general methodology can be adapted to other use cases in the future.

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 near-miss 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 whether the active signalized crossing light has been triggered. To increase processing speed, a frame-skip segment is included, which advances the reading in 10-s 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 s for this grade crossing. Frame-skip algorithms also allow for adaptability to high frame-rate video and reduce 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 check of the red pixel values in the small area

Figure 2. Stop signal under day and night conditions.

Table 1. Results for AI-Aided Detection of Near-Misses

Date	From	To	Duration (hours)	Red signals	Near-misses
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

Figure 3. Computer-recognized background using training data.

of the frame where the signal lies determines its status (Figure 2). 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 near-miss detection is activated.

Step 3: Background Template Learning. The near-miss 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 3).

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 Near-Misses. The algorithm identifies a near-miss 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 near-miss objectives from trains. If a near-miss 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 5 min and continues the analysis from Step 1. This 5-min 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.

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 near-miss events were detected on a 25-h video dataset, covering three different days. The processing time for this video was less than 40 min. A detailed summary is listed in Table 1.

The algorithm's output showed two near-miss events occurring within a single stop signal in the morning of one day. In the first near-miss, before the train arrived, two pedestrians entered the grade crossings while the stop signal was active (Figure 4*a*). Five seconds after the two pedestrians crossed the track, the train arrived. The second near-miss 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 4*b*).

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 in their ability to cross the track before the train arrived. The second case illustrates the assumption that no second train would cross, despite the presence of multiple

Figure 4. Two near-miss incidents detected by the AI algorithm.

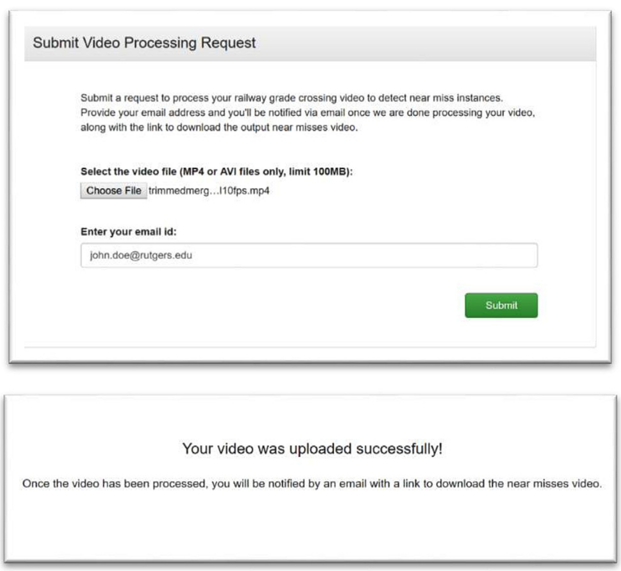

Figure 5. AI-Grade decision-support tool user interface.

tracks and the continuing signal. Both near-misses represent risky behaviors with potentially catastrophic consequences, which have been seen in past accident data (*12, 30*).

Wed-Based Decision-Support Tool (AI-Grade)

The AI algorithm described above has been implemented into a web-based decision-support tool called "AI-Grade" (Figure 5). The web-based AI-Grade streamlines the automatic processing of railroad grade crossing data through the following steps:

- Step 1: Log in to 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 complete, users will receive an email that provides the cropped near-miss video, if any.

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. There are four possible results: (1) an illegal trespass occurs, and a detection is recorded (correct); (2) no illegal trespass occurs, but a detection is recorded (false positive); (3) an illegal trespass occurs, but there is no detection (false negative); and (4) there is no illegal trespass and there is no resulting detection (correct).

For comparison, several students manually reviewed all the footage and compared their results 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 min, totaling 2% of the video time. We are further developing and training this algorithm using more video data (e.g., 1-year data) from our industry partners. Ultimately, we hope to design a tool for real-time analysis of video data in support of railroad safety decision-making.

Contributions to Research and Practice

Contribution to Academic Research

This paper describes an AI technological framework for automatically detecting near-misses 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

Table 2. Tool Validation Outcomes for Near-Miss Detection

	Trespassing	No trespassing
Detection	100%	0%
No detection	0%	100%

trespassing) from video big data because of an inordinate amount of human resources 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 (*31*). Similarly, we aim to empower AI to analyze a large amount of railroad video data for better understanding of human factors in various application scenarios.

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 about 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 the 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 near-misses or incidents in railroad systems, thereby improving their 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.

Conclusion

This paper proposes the use of a customized AI algorithm for automatically analyzing railroad video data to solicit useful information for understanding human behavioral characteristics. An example implementation and decision-support tool are developed based on grade crossing surveillance video data. In the study period, our AI algorithm correctly detected all the near-miss events associated with unsafe trespassing of the studied grade crossing. The near-miss data can be used to develop safety strategies and to prevent the occurrence of risk-prone behaviors and resultant accidents. This research indicates the promising applications of AI to other research areas in the railroad industry in the future, such as in-cab video analysis for distraction detection or security surveillance in railway stations.

Future Work

To take this research further we are increasing the volume of the training set to include more environmental conditions and possibly more near-misses. Once the AI algorithm is trained via a very large and diverse amount of video data, it can be used to "recognize" and "understand" a wide array of scenarios in real-time settings. Real-time video analytics in other locations and applications within the railroad industry will be developed, validated, and implemented. Another area of future research would be the analysis of video from the cameras installed in locomotives based on an adaptation of the AI algorithm described in this paper.

There are several major considerations when implementing a real-time system, some of which are as follows:

- Ethical: maintaining privacy of individuals in analysis and protection against sensitive data breaches;
- Economical: balancing costs and benefits of the technology;
- Accuracy: continually improving accuracy with a growing database;
- Demand: adding data types and metrics as per stakeholder request;
- Support: responding to system failures and correcting errors;
- Adaptability: ensuring the ability to perform under unforeseen or untested scenarios;
- Availability: maintaining access for stakeholders;

Additionally, a potential future step is to use the developed database for railroad safety risk analysis. As mentioned above, most previous studies were based on accidents instead of near-misses. If near-miss data can be collected, additional insights (particularly behavioral characteristics) could be drawn to further support railroad safety research (*9*). This would be combined with potential cost–benefit analyses to understand the practical value of AI implementation in the rail industry.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: AZ, XL, ZZ; data collection, analysis, and interpretation of results: AZ, XL, ZZ; draft manuscript preparation: AZ, XL, ZZ. All authors reviewed the results and approved the final version of the manuscript.

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