Enhancing the Safety and Reliability of Canadian Railways: Analysis of Highway Railroad Grade Crossing Accidents and Railcar Inspection Technology Assessment

by

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Abstract

The railway industry is one of the major contributors for the transportation of goods and the backbone of Canada's economy. Safe railway operation is vital for public safety, the environment, and property. Concurrent with climbing amounts of rail traffic on the Canadian rail network are increases in the last decade in the annual accident counts for derailment, collision, and highway railroad grade crossings (HRGCs).

The development of community areas near railway tracks increases the risk of HRGC accidents between highway vehicles and moving trains, resulting in consequences varying from property damage to injuries and fatalities. Also, the *2018 Railway Safety Act* showed concern over increasing trend of HRGC accidents and casualties. Thus, authorities have shown concerns about HRGC improving safety in rail network of Canada.

Various technologies have been used in the railway industry that improves decision-making, reduces errors, lower costs, save time and keep the safety of railway operation. Transport Canada, in the *2018 Railway Safety Act*, highlighted the incorporation of new technological innovations or Canadian railway network to enhance operation and reliability. One of such technological solution used for inspection of railcars is Train Inspection Portal System (TIPS). This system uses multiple camera systems with 360° images of railcars, which are then inspected by remote certified car inspectors (CCIs) and flag any defects/potential defects in the railcars of the trains. This technology is faster and better than manual inspections conducted by CCIs at rail yards.

The first study is focused on improving HRGC safety by identifying major factors that cause HRGC accidents and affect the severity of associated casualties using ExtraTree classifier method. Combining these causal factors and ensemble algorithms, machine learning (ML) models were

developed to analyze HRGC accidents and the severity of associated casualties that occurred between 2001 and 2022 in Canada. Furthermore, spatial autocorrelation and optimized hotspot analysis tools from ArcGIS software were used to identify hotspot locations of HRGC accidents on the railway network.

The second, third, and fourth studies of my research focus on technology assessment of the Train Inspection Portal System (TIPS). The second study employs a fuzzy-FMEA method, which uses machine learning to account for the imprecision and vagueness of real-life language, to conduct a risk assessment of the TIPS system. The study provides recommendations for reducing the risk of failure by addressing high RPN failure modes and enhancing the overall reliability of the TIPS system.

In the third study, we assess human factors in remote inspection tasks using the Human Factor Analysis and Classification System (HFACS) framework. The study identifies key HFACS elements that contribute to human errors in remote inspection processes and recommends strategies for reducing these errors and improving the overall quality of remote inspections. The fourth study aims to determine the detectability of rare railcar component defects in a TIPS technology environment and examines the response of remote CCIs. We performed simulations of artificial defects and supported the claim of human factors influence remote inspection performance.

This research is one of the small contributions to the railway network of Canada. The machine learning models developed to identify causal factors for HRGC accidents and severity of casualties can be used with future data to improve safety strategies. The assessment of POI technology using fuzzy-FMEA has identified high-risk causes of system failure and recommended control measures to improve reliability. Additionally, the artificial defect simulation and human factor assessment have highlighted the need to address rare defect capturing and the impact of human error on remote inspection performance. In summary, this research work has contributed to improving the safety of HRGC railway network and evaluating a futuristic technology that brings efficient, faster, and safer railcar inspection tasks. The findings of this study can improve policy and decision-making for railway safety and inspire future research in this field.

Preface

This thesis comprises two papers and two reports that I have co-authored with the principal investigators of the study, Drs. Lefsrud, Hendry, and Sattari. The primary focus of this thesis report is to achieve two objectives. Firstly, to evaluate the safety of highway railroad grade crossings (HRGC) using machine learning techniques. Secondly, to conduct a technology assessment of portal office inspection (POI) technology under the Automated Machine Vision Inspection System (AMVIS) project. The POI technology is used for remote inspection of railcars using a camera image which captures a 360˚ view of railcars.

In the first study on HRGC safety assessment, I worked in collaboration with Drs. Lefsrud, Hendry, and Sattari identify causal factors for safety assessment utilizing machine learning algorithms. To perform the safety analysis of HRGC accidents and casualties, I used data from the Government of Canada website and the Transportation Safety Board (TSB) website. Machine learning techniques were then applied to the collected data for analysis, and machine learning models were developed. The recommendations were also provided to improve the causal factors and improve the safety of HRGC.

The study for the technology assessment of POI technology was a collaborative effort involving Drs. Lefsrud, Hendry, and Sattari, contributed to the development of the methods for technology assessment. For the technology assessment, we performed a risk assessment of POI technology, human factor assessment and artificial defect simulation of rare defects. The risk assessment of POI technology involved a combined effort from Canadian Pacific Railways (CPR), National Research Council of Canada (NRC), and University of Alberta (U of A), with the fuzzy Failure Mode and Effect Analysis (fuzzy-FMEA) and rare railcar component defects simulation techniques being utilized. Dr. Lefsrud provided the HFACS framework and interview questions for identifying human factors in POI technology. I along with CP employees performed the rare defect simulation to analyze rare defects capturing of POI technology and to observe the response of remote certified car inspectors using POI technology.

Throughout the project, NRC and Transport Canada (TC) provided valuable insights. Arpit Patel, a U of A graduate student and I, conducted interviews with participants at CPR headquarters in Calgary. We both conducted 4 interviews to collect data. Also, I performed the simulation of artificial defects along with CPR employees in Alyth yard, Calgary. CPR provided necessary resources and facilities for the research work at their Calgary headquarters, and Alyth yard.

I analyzed all four datasets with support from Drs. Lefsrud, Hendry, and Sattari. As the lead author, I wrote both papers and reports, incorporating comments and feedback from the principal investigators.

Chapter 1 of this thesis, in its entirety, is my original work.

Chapter 2 of this thesis is submitted to the *Transportation Research Record* journal on February 21, 2023 and is under review. The data for this chapter was available on public websites. I was responsible for methodology, data analysis and manuscript composition. Drs. Lefsrud, Hendry, and Sattari provided assistance with data analysis, and contributed to manuscript edits.

Chapter 3 of this thesis is based on the risk assessment of POI technology. The experts of the technology contributed to the collection of data and data was used for performing the risk assessment. I was responsible for methodology, data analysis, and manuscript composition. Drs. Lefsrud, Hendry, and Sattari provided assistance with data analysis, and contributed to manuscript edits.

Chapter 4 of this thesis presents the human factor assessment of POI technology. Dr. Lefsrud played a crucial role in designing the interview process, which included three open-ended questions. I collaborated with Arpit Patel (U of A graduate student) to conduct the interviews with participants. The data was collected through these interviews and the responses were transcribed. I was responsible for the methodology, data analysis, and manuscript composition for this study. Drs. Lefsrud, Hendry, and Sattari provided valuable assistance with data analysis and contributed to manuscript edits.

Chapter 5 of this thesis presents a study on defect simulation on railcar components to assess the detectability of rare defects and the response of remote inspectors in the POI technology environment. The research involved simulating various railcar defects on the railcar components and collecting images from the POI technology software portal. Thanks to Chathula Adikari and Solange De Blois for helping us in performing the simulation experiment at Alyth yard, Calgary, and Dr. Alireza Roughani, Yan Liu and Transport Canada regional officers for their insights on defect simulation. I was responsible for the data collection, methodology development, data analysis, and manuscript composition. Drs. Lefsrud, Hendry, and Sattari provided valuable assistance with data analysis and contributed to manuscript edits.

Acknowledgment

I would like to express my deepest gratitude to my supervisors, Dr. Lianne Lefsrud and Dr. Fereshteh Sattari, for their unwavering guidance, support, and invaluable insights throughout my M.Sc degree program at the University of Alberta. Their expertise and dedication have been instrumental in shaping my ideas and approaches, and I am grateful for the opportunity to learn from them.

I would also like to extend my appreciation to Dr. Michel Hendry for his insightful comments and suggestions during the research process. In addition, I am grateful to Dr. Kyle Mulligan, Solange De Blois, Chathula Adikary, Brian Zou of Canadian Pacific Railway (CPR), Dr. Alireza Rouhani, Yan Liu, Noel Yves of National Research Council of Canada (NRC), and Khillian Kaveh, Christine Backs, Sasan Ebrahimi of Transport Canada Innovation Center (TC), for their valuable feedback, suggestions, and data collection opportunities. The financial support provided by Canadian Rail Research Laboratory (CaRRL) for this research project is also greatly appreciated.

I am deeply grateful to my parents, Bhartiben and Jayeshkumar, as well as my younger brother Harshil for their unwavering support and encouragement throughout this challenging and prolonged journey. Their love, patience, and understanding kept me motivated and focused on achieving my goals, and I am truly grateful for their constant presence in my life. Furthermore, I would like to express my gratitude to the Almighty for providing me with the unwavering strength and guidance to pursue my dream.

Finally, I would like to thank my friends and fellow research students for their friendship, compassion, and understanding. Your support and encouragement have made this journey more enjoyable and fulfilling.

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Chapter 1: Introduction

Introduction

Canada has a huge rail network, operated by numerous rail partners under challenging environmental conditions. The railroad industry plays an important role in the economy of the country. Hence, its safe working is crucial for the safety of all the stakeholders, the public, and the environment (Salas, 2022).

The accident statistics of the Transportation Safety Board of Canada (TSB) surfaced that more than 10000 accidents happened between 2011 and 2020 and were classified under main-track derailment, non-main track derailment, main track collision, non-main track collision, trespasser accident, crossing accidents, and fire/explosion accidents categories. All such accidents cause wide range of consequences which can result up to serious injuries and sometimes casualties (Rail Transportation Occurrences in 2020, 2020).

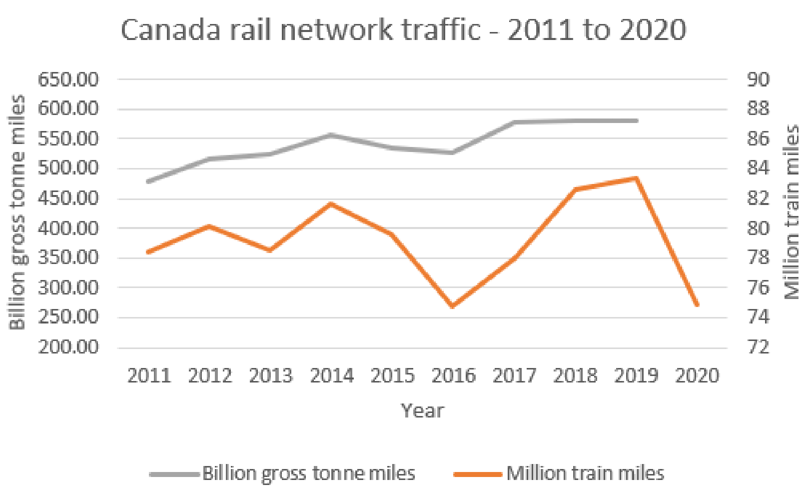


Figure 1. Rail network traffic of Canada (2011-2020)

The railway industry uses different metrics such as gross tonne miles (GTM) and passenger miles (PM) for defining tonnes of goods and passengers transported per year and per mile, respectively. Apart from these two, train mile (TM) is used to define the number of trains and length of travel, which measures the train traffic in sector. The Canadian railway network has shown an upward trend for train miles (TM) and gross tonne -miles (GTM) from 2011 to 2019 (Figure 1). There is a sharp drop in train miles for 2020 which is due to the impact of COVID-19 restrictions. At the start of the period, TM value was 78.4 million train miles which increased to 81.6 million train miles in 2014. However, it suddenly dived to 74.9 million train miles in 2016, which is the lowest for the period. The decrease in value is due to lower oil prices in the Canadian economy. After 2016, the TM value increased to 83.3 million train miles in 2019. Similarly, GTM value continued to rise from 478.2 billion gross train miles in 2011 to 581.25 billion gross miles in 2019. GTM value slightly decreased from 2015 and 2016 consecutively but it increased again from 2017 and onwards. GTM value for the year 2020 is not available for comparison.

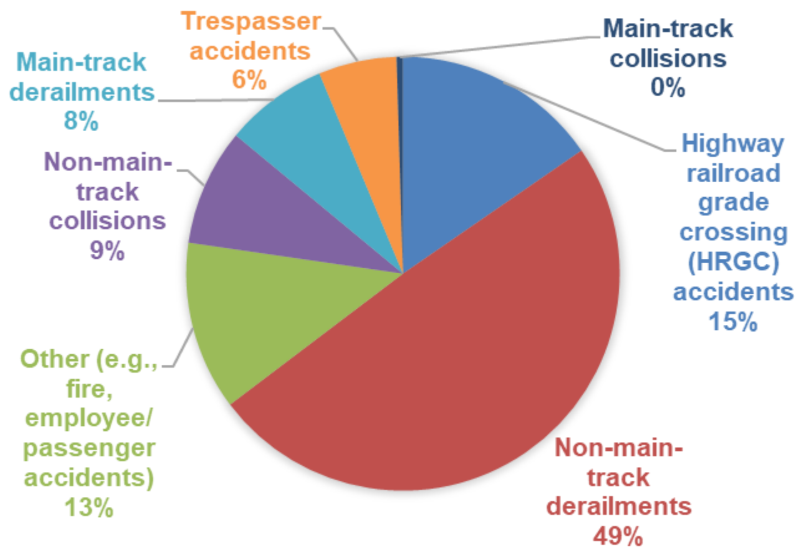


Figure 2. Percentage of railway accidents (2011-2020)

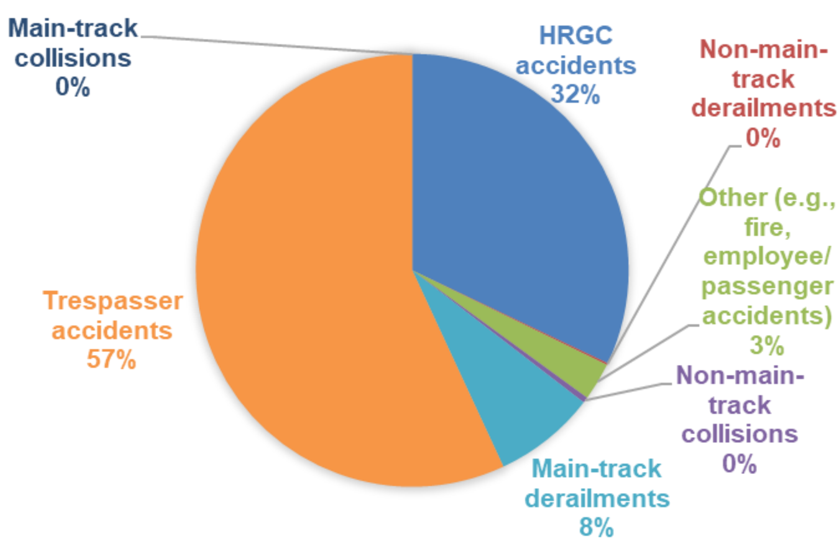


Figure 3. Percentage of railway fatalities in railway accidents (2011-2020)

Due to the large railway operation and high traffic on the rail network of Canada, it is susceptible to various kinds of railway accidents such as main track derailment, non-main track derailment, main-track collision, highway railroad grade crossing accidents, trespassing accidents, etc. Figure 2 shows the percentage of accident and Figure 3 shows the percentage of fatality in accidents for the rail network of Canada between 2011 and 2020.

Figure 2 depicts that non-main track derailment accident accounts for 49% of accidents followed by HRGC accidents (15%). When fatality data of Figure 3 were compared, it was found that trespasser accidents contributed to 57% of fatalities followed by HRGC accidents (32%). Upon comparing the two charts, it becomes evident that HRGC accidents have a high frequency and high consequences, making them a significant risk among all railway accidents. With the growth of residential neighborhoods near railway tracks, there is an increased possibility of HRGC accidents involving moving trains and highway traffic, which could result in severe consequences ranging from property damage to injuries and fatalities. The consequences of HRGC accidents are not only limited to the delay of rail traffic, property/environment damage, casualties but also have devastating effects on the people involved and their families, friends, responders, and locomotive operators. These accidents can result in severe psychological and social imbalances, leading to trauma and emotional distress. The *Railway Safety Act* review conducted by Transport Canada in 2018 highlighted the concern about the lack of decline in HRGC accidents and casualties, emphasizing the need for improved safety measures ("Enhancing Rail Safety in Canada: Working Together for Safer Communities," 2018). Consequently, railway authorities have been putting forth efforts to reduce HRGC accidents and improve safety.

My literature review on HRGC safety in the Canadian railway network revealed that current research has mainly focused on the causal factors associated with highways and railroads such as train speed, road speed, daily train and vehicle traffic, and number of highway lanes. Thus, my coauthors and I identified the gaps: (1) Despite efforts to improve safety measures, the rate of accidents related to grade crossings has not shown a significant decrease over the past few years and it has become a concern for the public (2) Despite current initiatives and investments aimed at improving grade crossing safety, they have not been sufficient in making a significant difference and implementing the safety strategies across every HRGC of the railway network is a huge and capital-intensive task.

To address the above-mentioned gaps, I conducted an analysis of HRGC accidents and casualties in the Canadian railway network. Using machine learning algorithms, ExtraTree classifier, I identified critical causal factors that contribute to HRGC accidents and the severity of casualties. My literature review on HRGC safety identified significant gaps in the literature, specifically in the identification of critical causal factors. Previous studies have largely overlooked the impact of human actions in HRGC accidents, the type of vehicles involved, seasonal and lighting variations, and the type of protection in place at HRGCs. These findings of causal factors can help in the development of safety strategies for HRGCs. Furthermore, we developed two classification models to analyze the HRGCs based on accident risk and severity of casualty. These models are useful classification tools that can also be used with future data as datasets get updated. However, focusing on all HRGCs is impractical, which highlights the need to identify high-risk locations. To address this, I chose to perform hotspot analysis using ArcGIS software, which enabled us to identify HRGC hotspots and concentrate safety efforts accordingly.

In this thesis paper, I provide recommendations on reducing the impact of critical causal factors to decrease the occurrence and severity of HRGC accidents. These findings can ultimately help making HRGCs a safer spatial area on the railway network.

The next three studies are focused on Portal Office Inspection (POI) technology which is a part of the Automated Machine Vision Inspection System (AMVIS). This project is the response of the *Railway Safety Act* which was reviewed by Transport Canada (TC) in 2018. In the review of *Railway Safety Act*, TC highlighted the crucial role that technology plays in ensuring safe railway maintenance and operation. As the railway industry moves towards a more technology-driven approach, it is expected that this trend will continue, providing opportunities to reduce risk, improve efficiency, and enhance overall safety.

The railway industry in Canada has made significant strides in developing and utilizing innovative safety processes and technologies. The railway companies have partnered with government and academic institutions for developing and testing various technologies such as imaging and drone technologies for the inspection of assets. Advancements in technology have demonstrated remarkable results in managing risks associated with rail maintenance and operations. For instance, in 2016, the percentage of derailments caused by equipment and track failure decreased from 66% to 57%, owing to the integration of technology and processes designed to enhance safety ("Enhancing Rail Safety in Canada: Working Together for Safer Communities," 2018).

In order to capitalize on the opportunities presented in *Railway Safety Act* review about technological advancements in Canada's rail sector, Transport Canada made several recommendations to improve railway safety. One of these recommendations was the creation of a specialized research and development group known as the Railway Research Advisory Board (RRAB). The purpose of this board is to prioritize and promote research initiatives in technology and innovation, with the ultimate goal of enhancing safety within the rail industry.

The Automated Machine Vision Inspection System (AMVIS) project is part of Transport Canada's response to the 2018 *Railway Safety Act* Review's recommendation on technology and innovation. The project is guided by RRAB which involves experts from different railway organizations, research organizations, and from federal departments as well. This team is providing guidance and technical support for AMVIS technology which is being developed by Canadian Pacific Railways (CPR).

According to regulations of TC, a railway company shall perform safety inspections to ensure that rail cars in a train consist are free from safety defects. These inspections are performed by certified car inspectors (CCIs) at rail yards where trains are made up, cars added to trains, or where cars are interchanged. However, in 2020, CPR got an exemption from TC to allow remote safety inspection (RSI) using high-resolution camera technology instead of traditional safety and maintenance (S&M) inspection on potash trains (602/603 and 618/619) as per inspection requirement. Train numbers 602/603 are bound between Sutherland, Saskatchewan, Canada, and ports of Vancouver, British Columbia (BC), Canada. And, with number 618/619 are bound between mining locations in Sutherland, Saskatchewan, Canada, and ports of Portland, Oregon, United States (US).

The AMVIS technology, at CPR, is consist of two technologies. (i) Wayside detector technology, and (ii) Portal Office Inspection (POI) technology. The wayside detector technology consists of different wayside detectors such as wheel impact load detector (WILD), Wheel Profile Detector (WPD), Hot Box Detector (HBD), and Trackside Acoustic Detector (TAD). These wayside detectors generate alerts for various defects in wheels, bearings, brakes, and trucks when the train passes over them. The POI technology uses Train Portal Inspection System (TIPS). The TIPS portal is located at milepost 85.66 in the Maple Creek subdivision (Figure 4). The TIPS is a system with high-definition infrared spectrum cameras that capture a 360-degree view of the railcar when a train passes through it. The TIPS has four sub-systems that capture the images of different target parts of railcars.

Figure 4. CPR's train inspection portals located at Maple Creek

1. TrainView system: It captures images of external components such as hand brake wheel, ladders treads, sill steps, car body condition, reflectors, foreign objects, car ID, etc. The system has 10 camera boxes with total of 20 cameras.

2. TruckView system: It captures components such as axle cap screw, wheel, side frame, bearing, springs, friction wedges, etc. The system has 4 camera boxes with total of 8 cameras.

3. CSCView system: It captures undercarriage components such as side sill, center sill, hopper doors, couplers, and related components, brake beams, axle, and journal components, etc. The system has a total of 8 lasers and 5 cameras.
4. AHView System: It captures defects related to peaked air hose coupling, coupler defects, retain key, etc. The system has 2 camera boxes with a total of 4 cameras.

The scope of defects in the AMVIS project is selected based on defects detection challenges, occurrence frequency, and potential impact on safety. We consulted TC inspectors and railway companies to decide the defects for the scope of AMVIS project. Finally, a total of 13 defects were selected for AMVIS scope:

1. Cracked wheel
2. Cracked axle
3. Axle cap screw missing
4. Truck bolster crack
5. Truck spring missing/bent
6. Brake beam bent
7. Side sill bent/cracked
8. Center sill cracked
9. Cracked coupler knuckle
10. Cracked draft gear
11. Coupler body crack
12. Hand brake
13. Angle cock

I conducted the literature review using AMVIS project documents, vendor/supplier documents, and research articles. The thesis work on the AMVIS project is primarily focused on evaluating the effectiveness of POI technology for defect capturing, rather than comparing the safety aspects of manual yard inspections versus remote inspections using POI technology. As we were conducting the technology assessment of POI technology, we also consulted the NRC, CPR and TC team to understand the technology and identified following gaps: (1) TIPS portal system gets affected due to various factors such as equipment failure, power failure environmental conditions which affects the reliability of TIPS operation; (2) Human errors affect the defect identification and quality of remote inspection using POI technology; (3) POI technology is effective in capturing high frequent defects such as hand brake, angel cock. broken truck spring) but response to rare defects (such as cracked draft gear, cracked side sill) is not very clear in POI based remote inspection.

To address the research gap regarding the reliability of TIPS portal operation, we employed a fuzzy Failure Mode and Effect Analysis (fuzzy-FMEA) to perform a risk assessment. This machine learning technique utilizes expert knowledge to determine the fuzzy Risk Priority Number (fuzzy-RPN) of identified failure causes. We analyzed the results of the assessment and identified the high-risk causes based on the fuzzy-RPN number. We then recommended additional control measures to reduce the risk of failure and improve the reliable operation of TIPS portal. The application of fuzzy-FMEA in this study provided a novel approach to addressing the research gap and improving the reliability of TIPS portal operation.
To identify the underlying causes of human error affecting the performance of remote inspection tasks in POI technology, we conducted a thorough human factor assessment. We utilized the elements of HFACS as codes and applied thematic analysis, a qualitative analysis technique, using Nvivo software. Dr. Lefsrud, along with the NRC team, formulated three questions to probe the root causes of human error, while Arpit Patel, a graduate student from the University of Alberta, and I conducted four interviews with remote CCIs. The resulting transcripts were meticulously analyzed to identify codes and themes using a hybrid approach of thematic analysis. Our study revealed that the "Technical Environment" was the most significant cause of human error in remote inspection using POI technology. The findings shed light on a critical area of improvement for the safe and efficient implementation of POI technology in the railway sector.

To assess the ability of POI technology in detecting rare defects, we conducted a simulation study using artificial defects created with metal wire, silicon caulk, and magnets. To better understand the methodology for artificial defect simulation, we reviewed relevant literature from organizations such as Transportation Technology Center, Inc. (TTCI) and the University of Illinois at Urbana-Champaign. Our simulation results revealed that POI technology is effective in identifying rare defects; however, during remote inspection of railcars, human inspectors still missed some of the defects. This finding reinforces the notion that human error can impact the quality of remote inspection technology.

The Canadian railway network has contributed significantly to the country's economy but safety remained a major concern for public safety, the environment, and railway operations in recent years. My research thesis was motivated by the 2018 *Railway Safety Act* review conducted by Transport Canada, which emphasized the to improve HRGC safety and need for technological advancements in the railway network to improve safety and efficiency in railways ("Enhancing Rail Safety in Canada: Working Together for Safer Communities," 2018). In my work on HRGC safety, I specifically targeted the Canadian railway system and identified causal factors for HRGC accidents and the severity of casualties, which had been overlooked in previous studies. Furthermore, I developed machine-learning classification models that can be used on new datasets in the future. I also utilized a hotspot analysis tool to visualize high-risk clusters for HRGCs. In addition, my work on TIPS technology evaluation under the AMVIS project used a quantitative risk assessment technique to assess the technology, conducted human error assessment using the HFACS framework, and simulated defect installations to examine rare defects and remote CCI response. Overall, my work on AMVIS assisted the project team in identifying failure modes of the TIPS portal, causes of human error in remote inspection tasks, provided insight into rare defect inspections, and developed a defect dataset for fully automated AI-machine learning-based technology for railcar inspection.

My final thesis has had a significant impact on the railway sector of Canada by contributing to the prevention of HRGC accidents and casualties, as well as promoting the integration of technological innovation for efficient and safer railway operations. I adopted a multidisciplinary approach to identify hazards and increase the visibility of risks associated with TIPS technology. Moreover, I uncovered crucial factors contributing to human error in remote inspection processes. The findings and recommendations of my thesis work provide targeted solutions to the issues faced by the railway sector of Canada and offer actionable insights to mitigate risks and manage hazards.

Chapter 2: A Machine Learning Approach to Enhance Highway Railroad Grade Crossing Safety by Analyzing Accident Data and Identifying Hotspot Accident Locations

Abstract

Safe railway operation is vital for public safety, the environment, and property. Concurrent with climbing amounts of rail traffic on the Canadian rail network are increases in the last decade in the annual accident counts for derailment, collision, and highway railroad grade crossings (HRGCs). HRGCs are important spatial areas of the rail network, and the development of community areas near railway tracks increases the risk of HRGC accidents between highway vehicles and moving trains, resulting in consequences varying from property damage to injuries and fatalities. This research aims to identify major factors that cause HRGC accidents and affect the severity of associated casualties. Using these causal factors and ensemble algorithms, machine learning (ML) models were developed to analyze HRGC accidents and the severity of associated casualties that occurred between 2001 and 2022 in Canada.

Furthermore, spatial autocorrelation and optimized hotspot analysis tools from ArcGIS software were used to identify hotspot locations of HRGC accidents. The optimized hotspot analysis shows clustering of HRGC accidents around major Canadian cities. The analysis of cluster characteristics supports the results obtained for causal factors of HRGC accidents. These research outcomes help to better understand the major causal factors and hotspot locations of HRGC accidents and assist authorities in implementing countermeasures to improve the safety of HRGCs across the rail network.

Keywords: Canadian rail network, Highway railroad grade crossing, SMOTE, Machine learning, ArcGIS

Introduction

The railway industry of Canada is a major contributor to the country's economy and the safety of the rail network is very crucial as accidents on railway network can seriously harm the system, environment, and result in numerous fatalities (Canada's Freight Railways: Moving the Economy, 2023; Ouedraogo et al., 2018). Canada's rail network is the third largest in the world, with more than 41,700 km of rail tracks featuring 25,155 highway railroad grade crossings (HRGCs) (Rail Safety in Canada, 2021; Grade Crossings Inventory, 2022). An HRGC is an intersection of railway tracks and roads at the same grade level (Grade Crossings Inventory, 2022). Accidents at HRGCs are a safety concern and have attracted the attention of transport authorities, the public, and the railway sector (Tey et al., 2013). The expansion of municipalities and the development of high-population areas near railway lines poses a greater risk of accidents that can result in fatalities, injuries, extensive property damage, and delays in railway and highway traffic, making HRGCs spatial areas of paramount importance for transportation safety (Lu & Tolliver, 2016; "Enhancing Rail Safety in Canada: Working Together for Safer Communities," 2018). Between 2011 and 2020, 10,705 railway accidents were recorded in Canada, with the leading categories being non-main track derailments (49.3%) followed by HRGC accidents (15.4%) (Table 1) (Rail Transportation Occurrences in 2021, 2021). A non-main track derailment is when one or more railcar wheels come off the rail surface on non-main tracks (such as yard rail lines). These accidents usually happen at speeds below 10 miles per hour and are hence considered low-consequence accidents (Rail Transportation Occurrences in 2021, 2021). On the other hand, accidents at HRGCs that include trains and highway vehicles are known as HRGC accidents (Highway-Rail Grade Crossings Overview, 2019). These accidents usually happen at track speed between vehicles and a moving train and are considered high-consequence accidents. According to the data in Table 1, the number of HRGC accidents (1,648) is less than the number of non-main track derailment accidents (5,278), but the fatality counts for HRGC accidents is far higher (227 vs. 1). Thus, HRGC accidents are considered higher risk than non-main track derailments and can result in more fatalities (Das et al., 2022).

Table 1. Rail accident based on accident type (2011-2020) (Rail Transportation Occurrences in 2021, 2021).

Type of accident	Accident count	Percentage	Fatality count

Non-main-track derailments	5278	49.30	1
Highway railroad grade crossing (HRGC) accidents	1648	15.40	227
Other (e.g., fire, employee/ passenger accidents)	1346	12.60	20
Non-main-track collisions	933	8.71	3
Main-track derailments	825	7.70	54
Trespasser accidents	625	5.83	403
Main-track collisions	50	0.47	0
Total	**10705**	**100**	**708**

Table 1 shows the time-trend analysis of HRGC accidents and associated casualties in Canada from 2011 to 2020. The analysis was conducted using accident and casualty counts from the Transportation Safety Board of Canada (TSB) dataset. For comparison purposes, these counts were normalized using million train miles (MTM) data for each year. HRGC accident counts per MTM have not changed much over the last decade (Figure 5a); however, fatality and serious injury counts per MTM have fluctuated. Fatality and serious injury percentages for HRGC accidents have both shown an overall decreasing trend in the last decade; yet, the percentage of fatalities (Figure 5b) and serious injuries (Figure 5c) caused by HRGC accidents is high, both at ~30% in 2020. HRGC accidents were the second-highest contributor to railway fatalities after trespasser accidents from 2011 to 2020; however, HRGC accidents have been the highest contributor to serious injuries on the Canadian railway in the last decade (Rail Transportation Occurrences in 2021, 2021).

Figure 5b shows a sudden drop in 2013 with respect to %HRGC fatalities. In 2013, a total of 47 fatalities were reported in "main-track derailment" category due to an accident in Lac-Mégantic, Quebec which resulted in a lower % of HRGC fatalities. Thus, the %HRGC fatalities value is considered an outlier for fatality data in 2013. Figure 1c shows the %HRGC serious injury experienced a sudden rise in 2013. The total serious injury count was 39 in 2013 and relatively fewer injuries were reported in other categories. This resulted in an unusually large contribution of HRGC accidents to the total. Thus, the 2013 value is considered an outlier for serious injury data (Rail Transportation Occurrences in 2021, 2021).

High occurrences and consequences of HRGC accidents have raised concern, resulting in many studies aimed at improving the safety of HRGCs. For instance, a study by Lu et al. (2018) uses generalized linear models such as the Poisson, Bernoulli, and Hurdle Poisson models, to predict HRGC accident frequency. The dataset contained crossing, highway, and rail traffic variables of HRGC accidents in North Dakota, United States (US), between 1996 and 2014. The study highlights variables such as average daily vehicle traffic, daily train traffic, warning system, nighttime through-train traffic, train maximum speed, and the number of traffic lanes on the highway as contributors to HRGC accidents. Mok & Savage (2005) use negative binomial regression on HRGC accident data from the US from 1975 to 2001. Two separate models are developed in their study, one for predicting the number of HRGC accidents and another for predicting the number of casualties that occurred in HRGC accidents. The results indicate daily train traffic and vehicle traffic increase the risk of HRGC accidents and fatality counts, while an active warning system, locomotives with ditch lights, and safety campaigns reduce the risk. Another study by Brod & Gillen (2020) developed two models for HRGC risk assessment. The authors use the zero-inflated negative binomial model to predict HRGC accidents and the multinomial regression model to find the probability of severity (fatal, injury, and no injury). The study shows significant relations between HRGC characteristics, warning devices, and traffic exposure in HRGC accidents. Brabb et al. (2017) studied HRGC accident data to analyze various factors in injuries and fatalities caused by HRGC accidents. The report identifies the effects of traffic, driver demography, environment, and crossing characteristics on the severity of casualties

Figure 5.Trends in (a) HRGC accidents, (b) fatalities, and (c) serious injuries (2011-2020) (Rail Transportation Occurrences in 2021, 2021)

in HRGC accidents. Soleimani et al. (2021) use federal railroad administration (FRA) data to develop an HRGC consolidation model for public crossings using text mining, spatial analysis, and an XGBoost algorithm to identify possible HRGCs that can be considered for closure in future.

Several recent studies employ ML models to improve the safety of HRGCs. For instance, Zheng et al. (2016) use ML to identify HRGC accidents based on accident risk in the US between 1996 and 2014. The classification model was developed using a decision tree (DT) and gradient-boosting (GB) algorithm and obtained good classification accuracies (0.7705) for accidents and no accident cases at HRGCs. The authors found factors such as daytime train movement, nighttime train movement, daily train traffic, train speed, and highway speed are the most important factors related to HRGC accidents. Another study by Lasisi et al. (2020) uses various ML classifiers, such as support vector machine (SVM), random forest (RF), gaussian naïve bayes (GNB), multi-layer perceptron-neural network (MLP-NN), and logistic regression (LR), to predict casualties resulting from HRGC accidents using HRGC casualty data from California, US. High prediction accuracy (0.989) is achieved with the SVM. A total of 15 features are taken into account, including features related to railway and highway traffic and crossing characteristics that revealed train speed, average daily train, and vehicle traffic are essential factors affecting casualties in HRGC accidents.

The spatial distribution and hotspot locations of HRGC accidents have been assessed using spatial autocorrelation and optimized hotspot analysis using ArcGIS software. These tools generate significant and valuable spatial analysis results by employing accident counts/rates and geographic data as inputs. The results of spatial autocorrelations and optimized hotspot analysis show the statistically significant locations on maps called hotspot locations of accidents. Various studies have been conducted to analyze aviation accidents and road accidents using different ArcGIS software. Y. Li & Liang (2018) performed a study for aviation accidents in Florida, US, using hotspot analysis tools and data from the National Transportation Safety Board (NTSB) for 2002 to 2017 and reports 75 hotspot locations for aviation accidents. Studies conducting spatial clustering of road accidents were undertaken by Prasannakumar et al. (2011) in India and Mulugeta Tola & Gebissa (2019) in Ethiopia using ArcGIS. The results of these studies give information on hotspot and coldspot locations, which provide insights for traffic management and accident reduction.

To the best of the author's knowledge, limited research has been conducted on HRGC accidents in Canada’s rail network. Many contributing factors are involved in HRGC accidents, including both highway and railway factors. The study performed by Heydari & Fu (2015) uses Canadian railway HRGC data (2008-2013) to assess the effects of HRGC location attributes. The study only investigates a few factors, such as train speed, road speed, daily train traffic, daily vehicle traffic, and number of highway lanes. Furthermore, a study by researchers at the University of Waterloo developed a tool called GradeX to assess HRGCs in Canada (Grade Crossings Inventory, 2022). It supports decision-making so authorities can identify high-risk HRGCs. The tool uses factors such as daily traffic of trains and vehicles, speed of trains and vehicles, location, and warning system at HRGCs. However, in both studies, important factors such as visibility, season, type of vehicle, and driver actions were not included. To address this research gap, all of these variables were considered in this research. This study focuses on identifying the most significant causal factors for HRGC accidents and the severity of casualties and helps in minimizing the chances and consequences in HRGC accidents. These causal factors are used with ensemble classifiers to analyze HRGC accidents based on accident risk and severity of associated casualties. The results can inform the implementation of strategies to increase HRGC safety in Canada. However, targeting all HRGCs within a rail network with respect to the implementation of safety strategies is a very wide scope and highly capital-intensive task. Thus, locating the hotspots of HRGC accident locations is beneficial in terms of allocating appropriate resources. ArcGIS software helps not only visualize the spatial distribution of HRGC accident locations but also locate hotspot locations. Information about hotspot locations and causes of HRGC accidents will contribute to quicker implementation of safety strategies and enhanced safety at HRGCs.

The main objectives of this research are to:

1. Identify the causal factors of HRGC accidents and the severity of associated casualties using a feature selection technique (ExtraTree classifier);
2. Apply ensemble-supervised ML algorithms (RF, AdaBoost, and XGBoost) to analyze HRGC accidents;
3. Apply ensemble-supervised ML algorithms (RF, AdaBoost, and XGBoost) to analyze casualty severity in HRGC accidents; and
4. Determine HRGC accident hotspot locations using ArcGIS software for Canada's rail network.

Methodology

Data for ML Model

The HRGC crossing information and accident data were taken from two public sources. The HRGC inventory data, which was collected from the Government of Canada website (Grade Crossings Inventory, 2022), was used in the analysis of HRGC accidents. The dataset contained information about HRGC accidents that occurred at every HRGC in the Canadian rail network. The original HRGC inventory dataset (Grade Crossings Inventory, 2022) contained 25,155 samples with 26 feature columns, such as the number of daily vehicles, number of daily trains, maximum road speed, maximum train speed, type of protection, and number of tracks at the HRGC.

The data containing information about the severity of casualties associated with HRGC accidents were taken from TSB's Railway Occurrences Database System (RODS) (Dataset from January 1983 - Transportation Safety Board of Canada, 2020), and were used in the severity of casualty analysis using the ML model. The dataset included information about casualties reported in HRGC accidents. The original dataset contained information of 6,581 HRGC accidents with 348 features, such as rank, HRGC ID, railway owner, region, province, number of daily vehicles. Figure 6 shows the methodology for this research.

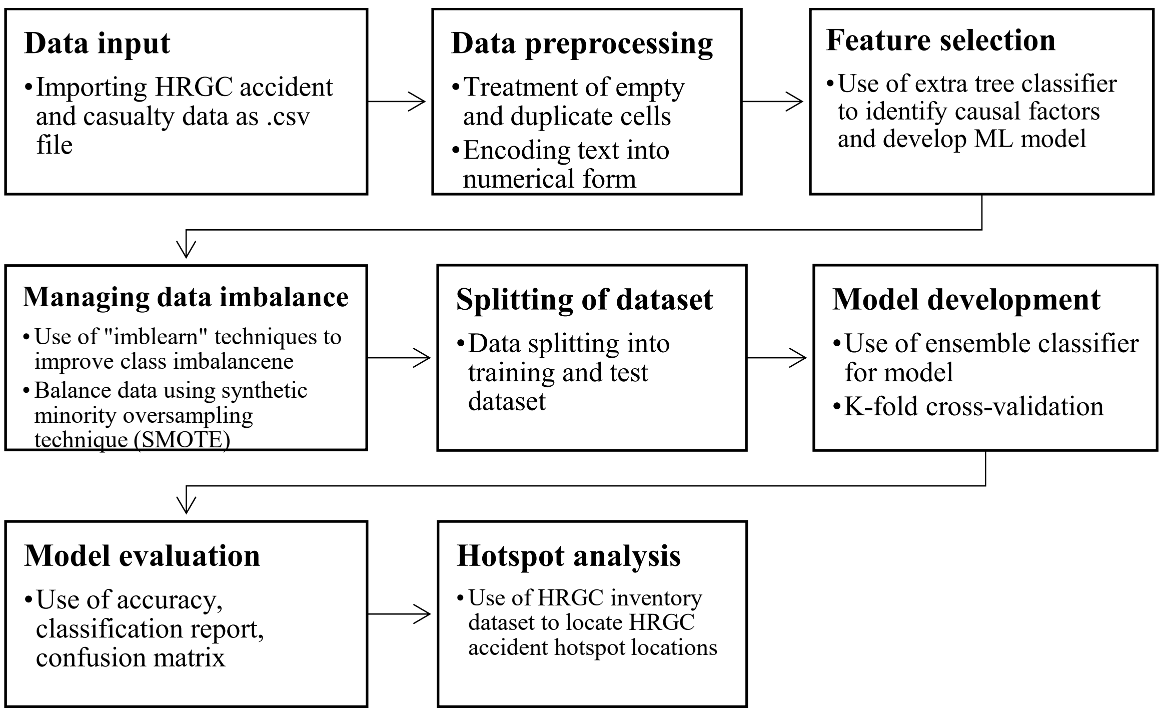


Figure 6. Methodology for supervised classification ML model

Data Preprocessing

The raw datasets from the data sources need preprocessing to address missing cell entries, duplicate rows, and categorical variables (Ajayi et al., 2020; Zhu et al., 2021). If not treated beforehand, these missing cell entries and duplicate rows in datasets cause biased performance estimation for the ML model. Techniques such as deleting rows with missing cells or entering arbitrary or mean values of the feature are commonly used to manage missing cell entries (Chorev, 2021). The datasets used in the present study contain many feature columns, including location, highway, railway, and environmental factors. However, some of the feature columns in the dataset had empty cells and therefore were excluded. In addition, duplicate row entries and feature columns with less important information were manually removed from the datasets.

The HRGC inventory dataset contained feature columns such as rank, Transport Canada (TC) number, railway owner, region, and province; these were removed because they added little value to the analysis (n=15). Thereafter, some sample entries were removed as they had empty cell entries (n=6,001). Categorical features such as "Access", "Protection", "Regulator", and "IsUrban" were converted to numeric variables using "LabelEncoder", which generated the matrix of data for the classification. Finally, 10 input features and one output feature were selected with 19,154 samples for feature selection. The output feature is a binary class feature, where 0 (zero) indicates an HRGC with no accident in history and 1 (one) indicates an HRGC with at least one accident reported in history. Definitions of each feature of the model are given in Appendix A.

The HRGC casualty dataset from RODS contained features such as railway owner, region, province, and subdivision that were not useful for the supervised classification model and, hence, were removed from the dataset. Additionally, some of the feature columns (such as dangerous goods released cars, ballast type, and temperature) were reported with many empty cell entries and therefore were also removed from the dataset (n=330). Furthermore, duplicate sample entries were removed from the dataset (n=174). Finally, after the data preprocessing, 17 input features and one output feature with 555 samples were selected. In addition, three more features were incorporated into the dataset to examine the effect of season, hour of the day, and train speed. The features named "Season" and "OccHour" were extracted using the time and date for given accidents from the dataset. The time was reported in "hhmm" format in the “OccTime" column. Thus, "OccHour" is extracted as "hh" from the "OccTime" column. "Season" is extracted from the "OccDate" feature column. The season of an accident was given a categorical variable, with 1 for winter (December to February), 2 for spring (March to May), 3 for summer (June to August), and 4 for fall (September to November). The “Train_Speed_MPH” feature was extracted using the HRGC-ID number, for the effect of train speed on casualties associated with HRGC accidents. The HRGC inventory dataset was used to extract train speed values based on the HRGC-ID for the RODS dataset. Output feature is a multi-class feature, where 0 (zero) indicates an HRGC accident with no serious injury, 1 (one) indicates an HRGC accident with atleast one serious injury, and 2 (two) indicates an HRGC accident with atleast one fatality. The final classification dataset had 20 input features and one output feature with 555 samples. Definitions of features are given in Appendix B.

Feature Importance by ExtraTrees Classifier

An ExtraTrees classifier is an ensemble method that helps identify the most important features for obtaining the output of the classifier (Arya et al., 2022). As a part of the ExtraTrees classifier, initial training samples are used to build each DT in the extra tree forest. Then, each tree is given a random sample of k features from the features at each test node. It must choose the best feature to divide the data according to a particular criterion (Gini index or entropy). The feature importance value ranges from zero to one, with higher feature importance values indicating features with a higher pertinence for predicting the output (Manoj, 2021a, 2021b).

Based on the output of the ExtraTrees classifier, the optimum number of features gets selected from the dataset for the classification model. According to the ranking of features in the ExtraTree classifier, an optimum number of features can be selected by assessing the accuracy value of the classification model for different numbers of features (Janecek et al., 2008). When less than an optimum number of features is selected, the model gives a low accuracy value for the classification model. When the number of features increases, the accuracy value increases. However, the accuracy value will not significantly improve after the optimum number of features is reached. The classification model takes a long time to train and test a dataset and can be computationally expensive when more than optimum features are selected (Kwon & Sim, 2013).

Data Balancing

Initial analysis of the datasets showed an imbalance in class distribution (i.e., one class label has a large number of observations, and the other has a small number of observations (Ajayi et al., 2020). Imbalanced datasets cannot be used for conventional classification algorithms because such algorithms are based on three main assumptions: (1) the use of the precision of the model for assessment criteria, (2) nearly equal distribution of classes in the dataset, and (3) the consequences of incorrect prediction of the class are identical for every class (J. Li et al., 2011). These assumptions are not valid for most real-world datasets, which often have an imbalanced distribution of classes (Ghofrani et al., 2022). High-performance classification models are built with a balanced dataset, which has near-equal sample counts of every class (Wei & Dunbrack, 2013). To balance the class distribution, advanced techniques from the "imblearn" package in Python, such as the oversampling technique, undersampling technique, and synthetic minority oversampling technique (SMOTE), are available (Tanha et al., 2020).

The oversampling technique increases the minority class samples by duplication and equalizes the class distribution but raises concerns about overfitting. On the other hand, the under sampling technique reduces the number of majority class samples, which leads to the omission of helpful information about a dataset (Handling Imbalanced Data Using Python, 2020). Another applicable technique is the introduction of synthetic samples around the existing samples, called the SMOTE, which creates minority samples by linear interpolating two identical classes using Eq. (1) and adding to the dataset (J. Li et al., 2011).

$$X_{New} = X_i + rand(0,1) \times (X_i - X_j) \tag{1}$$

The SMOTE approach uses sample X_i of a given class from the dataset and calculates the distance from neighboring identical classes. The neighboring sample X_j will be randomly selected to populate new X_{New} using Eq. (1). Hence, SMOTE can reduce overfitting and improve the classification model performance (J. Li et al., 2011). Therefore, SMOTE technique was used in our study.

Splitting of the Dataset

For supervised ML, datasets are divided into training and testing datasets using the "test_train_split" method with stratify parameter. This method divides the dataset according to the input ratio from the user and stratify parameter splits the dataset with an identical output class ratio in both the training and testing datasets. In this research, an 80:20 split ratio was used, meaning 80% of the data were partitioned into a training dataset and 20% into a testing dataset. In supervised ML, a training dataset is used to train the model, which allows the model to learn. After training, model performance is evaluated using the testing dataset (Kürs et al., 2020).

Classification Model Development

Ensemble classification algorithms were used in research to implement ML models. An ensemble classifier method is a meta-approach for improving the predictive performance of the ML model (Lu et al., 2020). Ensemble classifiers generate one optimal ML model by combining multiple base models. The ensemble method is advantageous because it guarantees the prediction and provides an ML model with high stability and resilience (Kurama Vihar, 2020). Vijaya & Sivasankar (2018) conducted a comparison study of ensemble and conventional classifiers to predict telecommunication customer churn. The outcome identified that the accuracy of ensemble classifiers, such as boosting and bagging, is greater than traditional classifiers. Hence, this research utilizes several ensemble-supervised ML classification models, such as RF, AdaBoost, and XGBoost.

The RF classifier employs DTs as individual models and uses bagging as an ensemble method (L. Chen, 2019). Bagging is fitting several models to various samples of the same dataset and averaging the resulting predictions (Kurama Vihar, 2020). The algorithm develops many trees, which happens in parallel, and then these trees vote for the most popular class (Nikulski, 2020). The algorithm has two phases: the first is the development of the RF, and the second is the prediction of results from the RF developed in earlier stages. As RF uses the bagging method, it helps to reduce overall variance by combining the results of several classifiers trained on various training data samples. The RF classifier requires considerable computational power and time for training the model, as it creates several DTs to integrate their outputs (Yamini, 2021). For RF, the greater the number of trees, the better result of the model. One fundamental problem that can worsen the results of the RF algorithm is overfitting. However, when the RF classifier has sufficient trees for the model, then the outcome of the model is not prone to overfitting (Gupta & C, 2021).

The AdaBoost classifier employs DTs as individual models and uses boosting as an ensemble method. Boosting is the repetitive application of a weak learning algorithm to different distributions over the training data and then merging of the weak learner's classifiers into a single composite classifier. AdaBoost is one of the popular ensemble ML methods that target misclassified instances in a previous weak classifier while training a new weak classifier. Obtaining high accuracy in the classification model is a primary objective; however, achieving high accuracy with only one classifier may not be possible. This problem can be rectified when multiple weak classifiers are employed, as each one gradually learns from the misclassified samples of the previous classifier. When training a new weak classifier, the weights of training samples are changed to improve learning. The weights are increased (decreased) for training samples that are incorrectly (correctly) classified in weak classifiers (An & Kim, 2010). The

AdaBoost algorithm is easy to implement, flexible, and prone to overfitting. However, it is sensitive to noisy data, outliers and takes longer to train as it trains the weak classifiers one by one (T. Chen & Guestrin, 2016).

Extreme gradient boosting (XGBoost) is a supervised ensemble ML algorithm that uses gradient-boosted DT as a model and boosting as an ensemble method (An End-to-End Guide to Understand the Math behind XGBoost, 2020). The input variables are assigned weight factors used by5 gradient-boosted DT to predict the results. Variables that the previous weak learners incorrectly anticipated are given more weight before being placed into the following DT. The models trained with this approach provide a more accurate and more potent model for ML applications (XGBoost, 2022). The model is popular due to its ability to manage sparse data as well as parallel and distributed computing while handling large samples (T. Chen & Guestrin, 2016). By incorporating regularisation parameter, learning rate, and column subsampling, the XGBoost lessens overfitting and improves in terms of speed and performance. Compared to AdaBoost, XGBoost is more challenging to comprehend, visualize, and tune. The XGBoost model requires significant resources to train and even to tune the model to get significant results.

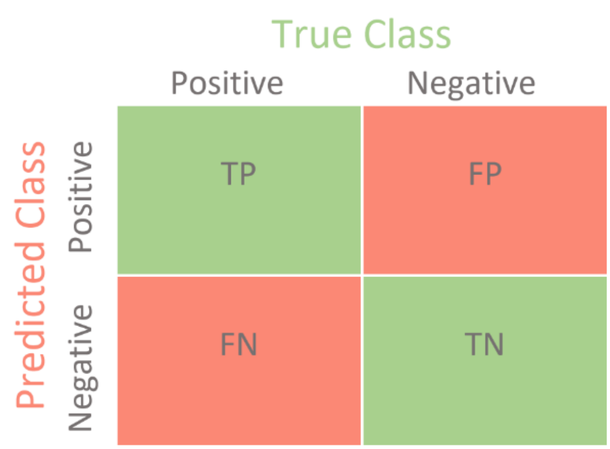


Figure 7. Confusion matrix for binary classification (Mohajon, 2020)

Performance Assessment Using Evaluation Metrics

Classifier models were evaluated using performance metrics, such as confusion matrix, classification reports, and accuracy. The confusion matrix is a table that is frequently used to describe how a classification model performed on the test data. The confusion matrix provides the counts for true positive, false positive, false negative, and true negative (Figure 7) (Mohajon, 2020).

A classification report is simply a consolidated representation of precision, recall, F1-score, and support values of the testing dataset for the classifier model. The equations for precision, recall, and F1-score are given in Eqs. (2-4). The macro average in the classification report indicates the mean value of the evaluation parameters (precision, recall, and F1-score). However, the weighted average in the classification report indicates the weighted value of the evaluation parameter by multiplying the respective proportion of each class in the test dataset (M, 2019). Accuracy is a ratio of correctly predicted observations to total observations (Eq. (5)). In this research, the K-fold cross-validation technique is used with K=10. The use of cross-validation helps to eliminate overfitting and underfitting scenarios. It also generalizes the model accuracy for any independent data (Wong & Yeh, 2020). A classification model must have high accuracy, high precision, high recall, and high F1-score values to be called a high-performance classifier (Mohajon, 2020).

The algorithms described above were implemented using Python version 3.9.7.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

$$F1 - score = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{4}$$

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + False\ Negative + True\ Negative} \tag{5}$$

Hotspot Analysis of HRGC Accidents

Hotspot analysis is an advanced technique to identify hotspot locations using incident/accident data. This approach is superior to existing techniques for identifying accident frequency, rate, and density. In this research, hotspot analysis was conducted by incorporating two tools included in ArcGIS software: (1) spatial autocorrelation (Moran's I method) and (2) optimized hotspot analysis.

Spatial Autocorrelation (Moran's I method)

The spatial autocorrelation method uses global Moran's I statistics, which consider feature values and location coordinates. Moran's I was one of the earliest measures of spatial autocorrelation globally and is still used to assess spatial autocorrelation (Eq. (6)). The spatial autocorrelation tool provides results that include Moran's I, Z-score, p-value, etc. (Spatial Autocorrelation (Global Moran's I) (Spatial Statistics)—ArcGIS Pro, 2020). Moran's I helps identify spatial patterns such as random, dispersed, or clustered, while the Z-score and p-value help determine statistical significance and reject or accept the null hypothesis (Prasannakumar et al., 2011). Moran's I can be calculated using the following equation:

$$I = \frac{N \sum_i \sum_j W_{i,j} \times (X_i - X) \times (X_j - X)}{(\sum_i \sum_j W_{i,j}) \sum_i (X_i - X) \times (X_j - X)^2}, \tag{6}$$

where N is the number of samples, X_i is the variable value at one location, X_j is the variable value at another location, X is the variable's mean, and W_{ij} is a weight applied to the comparison between locations i and j.

A Moran's I value near +1 indicates clustering (positive spatial autocorrelation) and near −1 indicates dispersion (negative spatial autocorrelation); a value of zero indicates a random (no spatial autocorrelation) distribution. In some cases, when the Z-score is extensive, but the significance value indicates rejection of the null hypothesis, Moran's I needs to be assessed. The result displays a clustered pattern if the Moran's I value is greater than 0 and a dispersed pattern if the Moran's I value is less than 0 (Prasannakumar et al., 2011).

Optimized Hotspot Analysis

Optimized hotspot analysis is an ArcGIS software tool that helps search for the region with a high concentration of occurrences within a defined limit (Prasannakumar et al., 2011). Optimized hotspot analysis is similar to the hotspot analysis tool but uses a parameter from the input data to run Getis-Ord Gi* statistics such as counts of accidents and counts of fatalities. The results provide statistically significant spatial clusters of the hotspots (high-value points) and coldspots (low-value points). This tool operates by examining each characteristic and considering its surrounding feature points. The outcome of optimized hotspot analysis gives a GiZScore and GiPValue for every sample of the dataset. These values help analyze the statistical significance and spatial clustering of the samples using Eqs. (7-9). The features with a high GiZScore and a low GiPValue indicate hotspots or high-value clustering locations, while features with a low GiZScore and low GiPValue indicate coldspots or low-value clustering locations (How Hot Spot Analysis (Getis-Ord Gi*) Works—ArcGIS Pro, 2020; Prasannakumar et al., 2011).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - X \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}{}^2 - (\sum_{j=1}^{n} w_{i,j})^2}{n-1}}} \tag{7}$$

$$X = \frac{\sum_{j=1}^{n} x_j}{n} \tag{8}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j{}^2}{n} - (X)^2} \tag{9}$$

where G_i^* is the Z-score for analysis, x_j is the attribute value of feature j, $w_{i,j}$ is the spatial weight between features i and j, and n is the total number of features. X is mean centre and S is the standard deviation of all measurements.

Results

Feature Selection for HRGC Accident Data

Figure 8 shows the importance of each feature of the HRGC accident dataset generated by the ExtraTrees classifier. "Vehicles_Daily" is the most contributing feature and "Access" the least contributing feature.

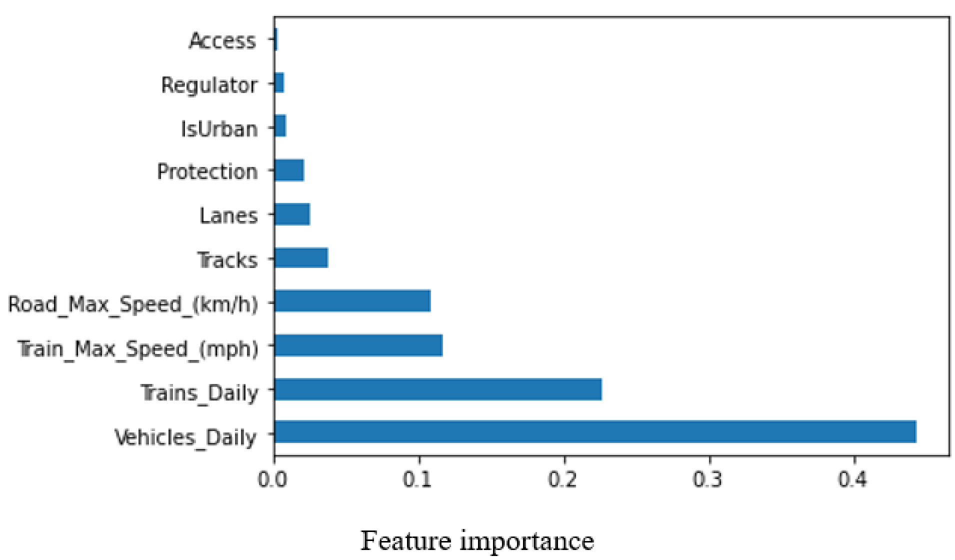


Figure 8. Feature importance for HRGC accident causes

Feature Selection for Severity of Casualties in HRGC Accident Data

Figure 9 shows the importance for each feature with respect to severity of casualties associated with HRGC accidents as obtained by the extra trees classifier model. "Train_Speed_MPH" is the most contributing feature and "NumberTrainsInvolved" the least contributing feature.

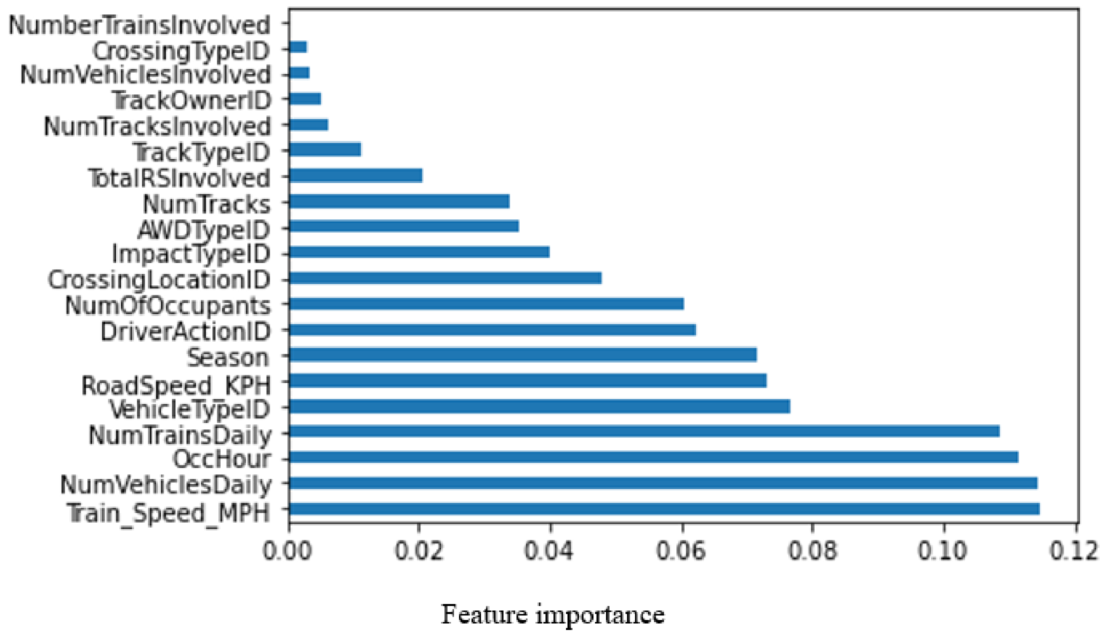


Figure 9. Feature importance for the severity of casualty causes

Analysis of Results of Classification Model of HRGC Accidents

The HRGC accidents classification model was developed using features obtained from the feature selections, with the feature importance of each feature (Figure 8) considered in the model. The model accuracies were compared using a different number of features (based on the output of the ExtraTrees classifier) to obtain the optimum number of features for the classification model. The highest accuracy was obtained with the top seven features of the dataset, as reported in Table 2.

Table 2. Features for the analysis of HRGC accidents

Input features	**Output feature**
Trains_Daily, Vehicles_Daily, Train_Max_Speed_(mph), Road_Max_Speed_(km/h), Lanes, Tracks, Protection	0 for an HRGC with no accident in history 1 for an HRGC with at least one accident in history

The classifiers were then evaluated using the mean accuracy of the classifier models (value of accuracy after K-fold cross-validation) (Lasisi et al., 2020). The highest mean accuracy value was obtained with the XGBoost (0.90), followed by the RF (0.87) and AdaBoost (0.82) classifiers.

Performance parameters (precision, recall, and F1 score) for the XGBoost classifier are reported in Table 3. Both classes (0 and 1) show high accuracy, high precision, high recall, and high F1-score with XGBoost classifier.

Table 3. Classification report for XGBoost classifier for HRGC accidents

Class	Precision	Recall	F1-score	Support
0 (no accidents)	0.95	0.98	0.96	3718
1 (at least 1 accident)	0.98	0.95	0.96	3718
Accuracy	-	-	0.96	7436
Macro avg	0.96	0.96	0.96	7436
Weighted avg	0.96	0.96	0.96	7436

Analysis of Results of Classification Model of the Severity of Casualties Associated with HRGC Accidents

The classification model was developed using features obtained from the feature selections, with the feature importance of each feature (Figure 9) considered in model. The model accuracies were again compared using a different number of features (based on the output of the ExtraTrees classifier) to obtain the optimum number of features for the classification model. The highest accuracy was obtained with the top 11 features of the dataset, as reported in Table 4.

Table 4. Features for the analysis of severity of casualties associated with HRGC accidents

Input features	Output feature

Season, OccHour, ImpactTypeID, CrossingLocationID, NumTrainsDaily, NumVehiclesDaily, RoadSpeed_KPH, DriverActionID, NumOfOccupants, VehicleTypeID, Train_Speed_MPH	0 for an HRGC accident with no serious injuries 1 for an HRGC accident with at least one serious injury 2 for an HRGC accident with at least one fatality

The classifiers were then evaluated using the mean accuracy of the classifier models (value of accuracy after K-fold cross-validation) (Lasisi et al., 2020). The highest accuracy was obtained with XGBoost (0.79), followed by the RF (0.75) and AdaBoost (0.53) classifiers.

The performance parameters (precision, recall, and F1 score) for the XGBoost classifier are reported in Table 5. All three classes (0, 1, and 2) show high accuracy, high precision, high recall, and high F1-score with XGBoost classifier.

Table 5. Classification report for XGBoost classifier for severity of casualties associated with HRGC accidents

	Precision	**Recall**	**F1-score**	**Support**
0 (no serious injuries)	0.80	0.74	0.77	77
1 (at least one serious injury)	0.87	0.88	0.86	77
2 (at least one fatality)	0.81	0.86	0.84	76
Accuracy	-	-	0.83	230
Macro avg	0.83	0.83	0.83	230
Weighted avg	0.83	0.83	0.83	230

Results of Hotspot Analysis

The hotspot analysis of the HRGC accidents was conducted using the HRGC inventory dataset. The dataset contained accident counts at different HRGCs across the rail network with GPS coordinates of each HRGC. The spatial autocorrelation of the dataset resulted in a z-score value of 8.1851, p-value of zero, and Moran's I more significant than zero (0.0116), which together indicate positive spatial autocorrelation and spatial clustering of HRGC accidents in the rail network (Lakshmi et al., 2019). The data are distributed as clusters for the rail network, which can be helpful for further analysis of causal factors of HRGC accidents for each cluster.

After obtaining the clustering distribution of HRGC accidents, optimized hotspot analysis was applied. The results of the optimized hotspot tool identified a total of 1,514 hotspot locations (with 99% confidence) of HRGC accidents in Canada's rail network (Figure 10).

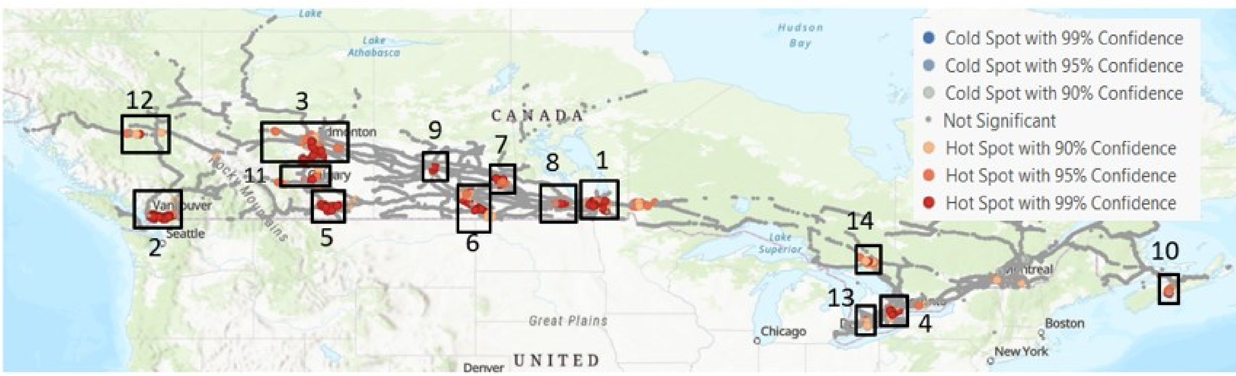


Figure 10. Hotspot locations for HRGC accidents with cluster number

The details of hotspot locations were used to define different clusters based on their location across the rail network (Table 6).

Table 6. HRGC accident cluster details

No.	Cluster number	Cluster area	Location counts
1	Cluster 1	Winnipeg	394
2	Cluster 2	Vancouver	354
3	Cluster 3	Edmonton	232

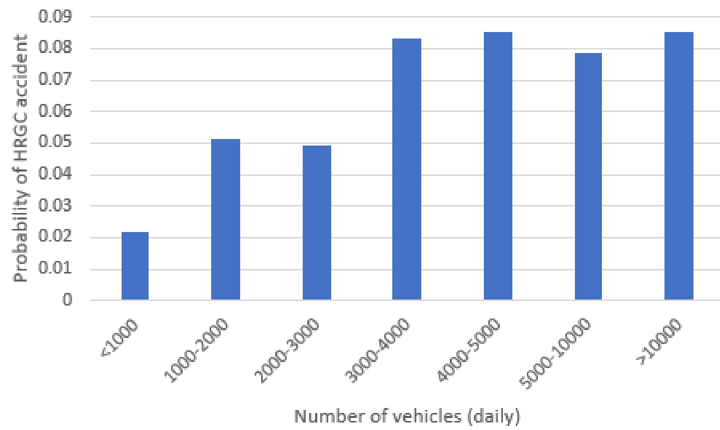
4	Cluster 4	Toronto	190
5	Cluster 5	Lethbridge	117
6	Cluster 6	Regina	93
7	Cluster 7	Yorkton	45
8	Cluster 8	Brandon	35
9	Cluster 9	Saskatoon	18
10	Cluster 10	Halifax	17
11	Cluster 11	Calgary	16
12	Cluster 12	Prince George	1
13	Cluster 13	Sudbury	1
14	Cluster 14	London	1
Total hotspot locations (with 99% confidence)			**1,514**

Discussion of Results

Causes of HRGC Accidents

According to Figure 8, the most important causal factor of HRGC accidents is "Vehicles_Daily", which is the number of road vehicles per day over a given HRGC. An assessment of crossing inventory data shows the probability of HRGC accidents increases as the number of daily vehicles increases for HRGC (Figure 11a). The second most influential factor for HRGC accidents is "Trains_Daily", which is the number of trains per day over a given HRGC. Figure 11b shows the probability of HRGC accidents for different daily train counts and indicates a positive relation with daily train count.

a)



b)

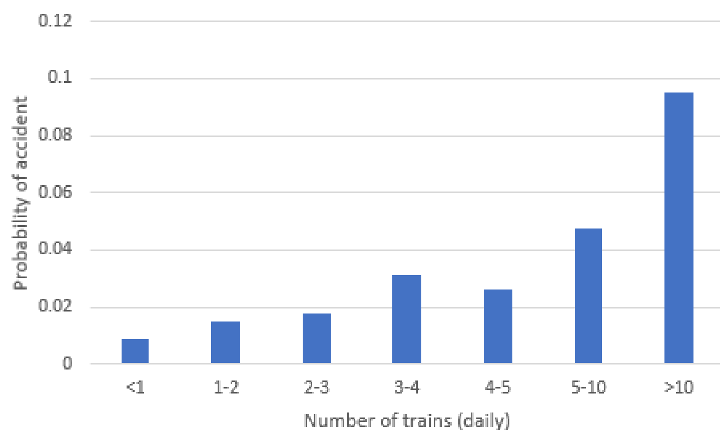
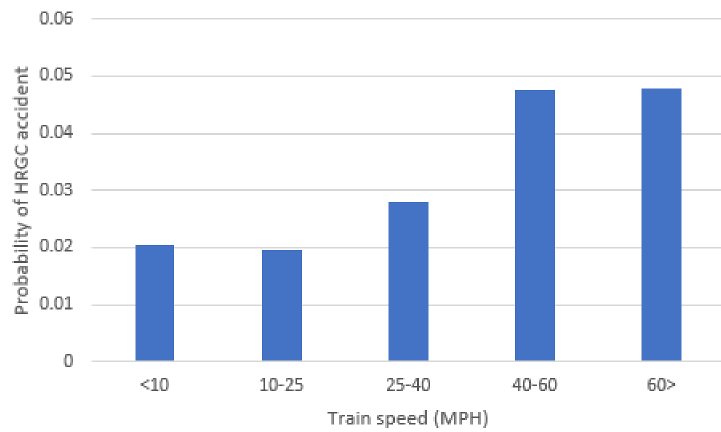


Figure 11. HRGC accident probability vs. (a) vehicles daily and (b) trains daily

Train_Max_Speed_(mph) is the third most influential causal factor for HRGC accidents. The fourth most important causal factor for HRGC accidents is Road_Speed_(km/h). Upon assessment of HRGC inventory data, the probability of HRGC accidents increases with an increase in train speed and road speed (Figure 12a, 12b).

a)



b)

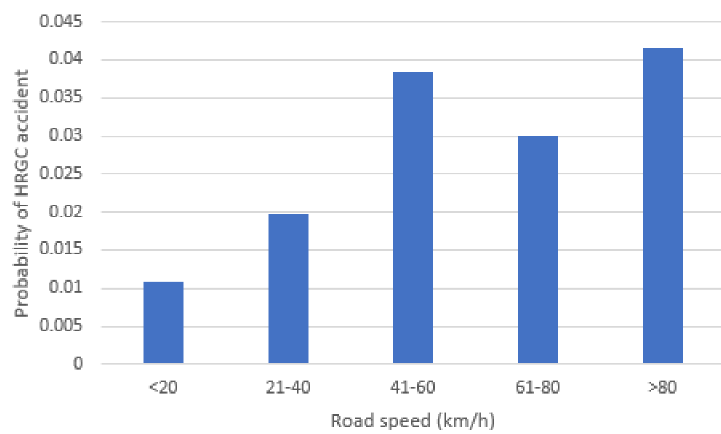


Figure 12. HRGC accident probability vs. (a) train speed and (b) road speed

The fifth most important causal factor of HRGC accidents is "Tracks", which means the number of rail tracks at an HRGC. Figure 13a shows the probability of HRGC accidents rises with an increase in track numbers at HRGCs. "Lanes" on the highway are the sixth most important cause of HRGC accidents. Similar to the number of rail tracks, the probability of HRGC accidents increases with an increase in the number of lanes at HRGCs (Figure 13b).

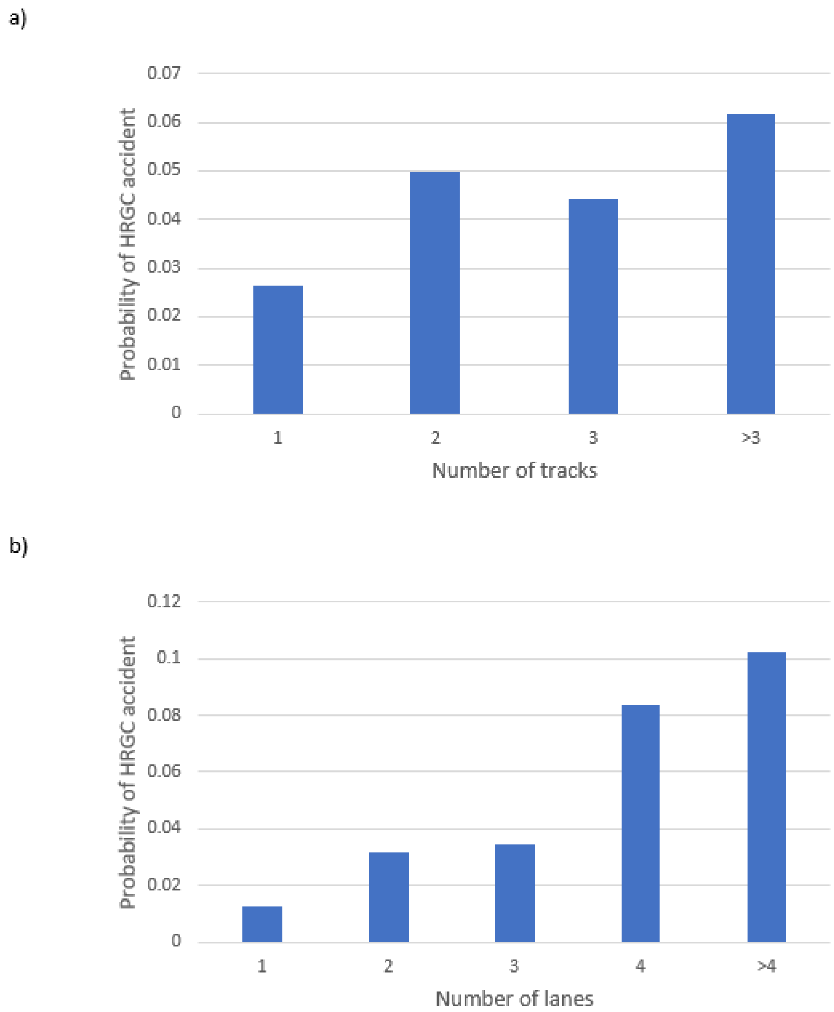


Figure 13. HRGC accident probability vs. number of (a) tracks and (b) lanes

"Protection" is the seventh most important causal factor for HRGC accidents and refers to the type of protection device installed at HRGC. The data from Canadian railways show 45% of HRGC accidents happen at passive crossings, followed by 30% at crossings equipped with flashlights, gates, bells, and 25% at crossings equipped with flashlights and gates. These data indicate protection devices at HRGC help to reduce the number of HRGC accidents.

Causes of Severe Casualties Associated with HRGC Accidents

The most important causal factor for the severity of casualties associated with HRGC accidents is "Train_Speed_MPH". Figure 14 shows the probability of accidents at HRGCs with fatalities and serious injuries increases with train speed. The figure also shows the probability of serious injury is less at higher train speeds compared to the probability of fatality, likely due to higher train speeds resulting in more fatalities.

Figure 14. Effect of train speed on the probability of severe injury or fatality associated with an HRGC accident

The second most important causal factor for the severity of casualties associated with HRGC accidents is "NumTrainsDaily", which indicates the number of trains passing over the given HRGC. Figure 15 indicates the probability of a fatal accident increases with an increase in daily trains, with the highest probability of a fatal accident associated with >25 daily trains. The probability of serious injury accidents varies with daily train count, with the highest probability associated with 5-10 daily trains at HRGCs.

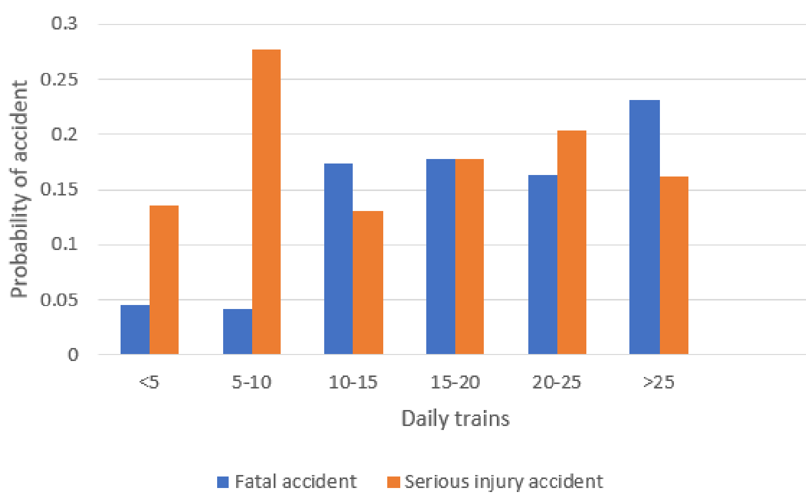


Figure 15. Effect of number of daily trains on the probability of severe injury or fatality associated with an accident at an HRGC

"NumVehiclesDaily" is the third influential causal factor for the severity of casualties associated with HRGC accidents, and refers to the number of vehicles crossing over a given HRGC. Figure 16 shows the probabilities of fatal and serious injury accidents both vary over the range of daily vehicles. The highest probability of a fatal accident is observed for <1,000 daily vehicles and the highest probability of serious injury accidents is observed for 1000-2000 daily vehicle.

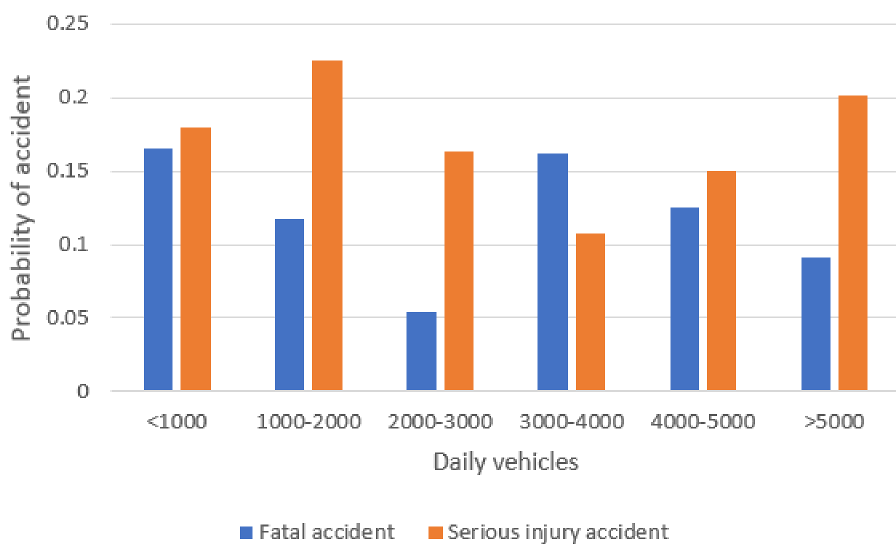


Figure 16. Effect of number of daily vehicles on the probability of severe injury or fatality associated with an HRGC accident

"OccHour", the hour of the day when an accident occurred, is the fourth most important causal factor for the severity of casualties associated with HRGC accidents. Figure 17 shows the probability of fatal and serious injury accidents varies with the time of day and is highest between 06:00 and 18:00. This is likely due to factors such as high volumes of commuter traffic, traffic jams/impatience, and sleepiness in the late afternoon. A high probability also occurs between 18:00 and 23:00 and is likely due to factors such as low visibility, slower reaction time, and tiredness (Hao et al., 2016).

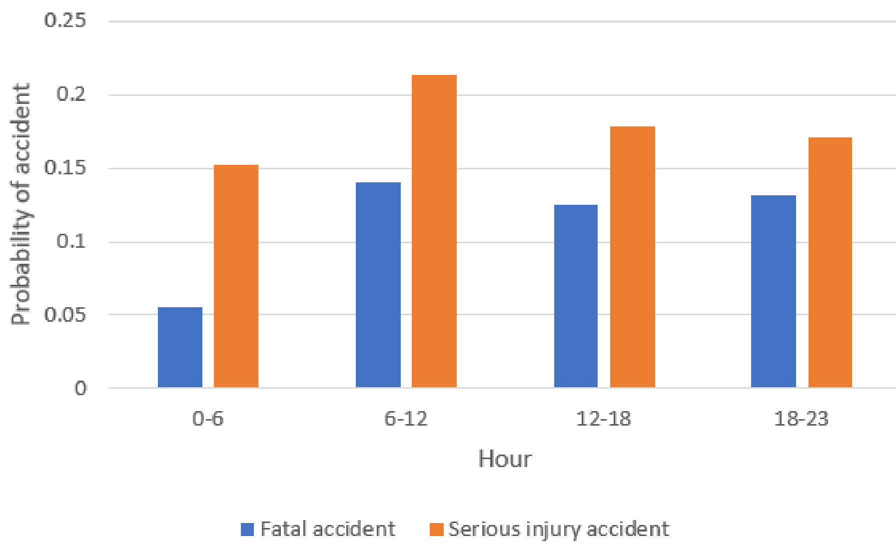


Figure 17. Effect of hour of the day on the probability of severe injury or fatality associated with an HRGC accident

The fifth most influential causal factor is "VehicleTypeID", which refers to the type of vehicle involved in the accident. Figure 18 shows the probability of a fatal accident is highest for motorcycles, followed by bicycles and automobiles, and the probability of serious injury is highest for motorcycles, followed by heavy trucks and bicycles.

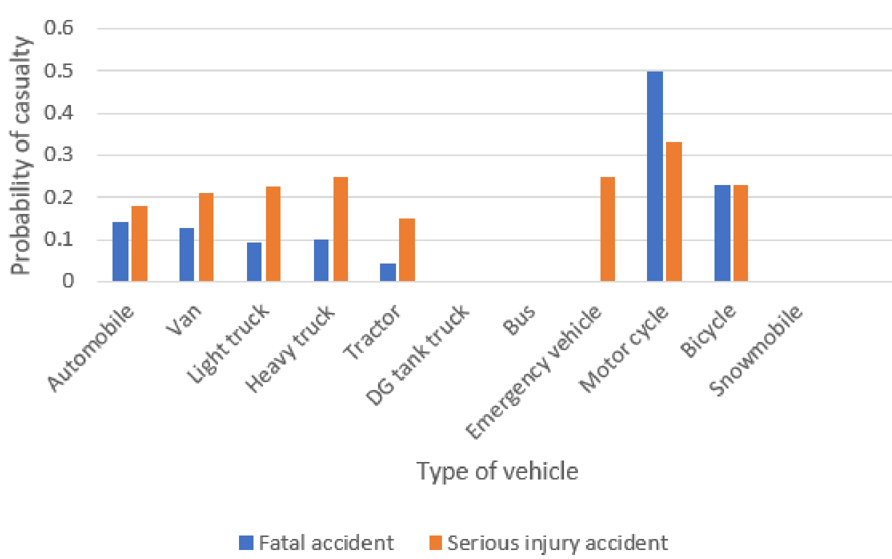


Figure 18. Effect of vehicle type on the probability of severe injury or fatality associated with an HRGC accident

"RoadSpeed_KPH" is the sixth most important feature and refers to the maximum road speed at an HRGC. Figure 19 indicates the number of both fatal and serious injury accidents increases with maximum road speed.

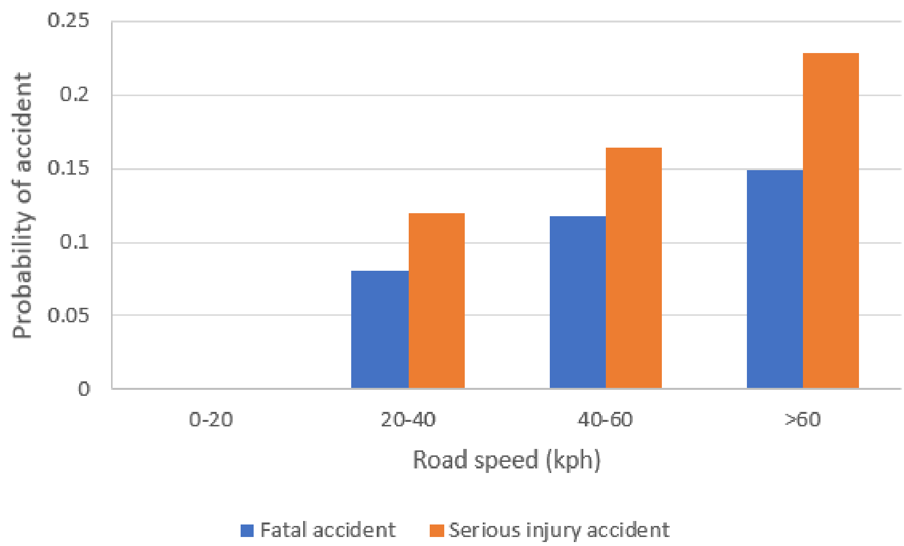


Figure 19. Effect of road speed on the probability of severe injury or fatality associated with an HRGC accident

The seventh most important causal factor that affects the severity of casualties associated with HRGC accidents is "Season". Table 7 shows that highest number of fatal and serious injury accidents happen in winter conditions and the lowest number in the fall. Weather conditions such as low visibility, presence of snow, and poor road conditions are contributing factors to high severity accidents in the winter (Singh et al., 2021).

Table 7. Effect of season on the severity of casualties associated with HRGC accidents

Season	Fatal accident	Serious injury accident
winter	31	49
spring	15	19
summer	18	22
fall	7	12

Discussion of Hotspot Analysis Results

Figure 10 and Table 6 show major accident-prone clusters are located near major cities. The top three HRGC accident hotspot clusters are located near Winnipeg (cluster-1), Vancouver (cluster-2), and Edmonton (cluster-3), with 394, 354, and 232 HRGC accident hotspot locations, respectively.

The characteristics of cluster-1 were examined based on the HRGC features examined earlier (§3.1). This assessment of cluster characteristics shows that of these HRGCs: 1) 50% were equipped with passive protection and 50% with active protection equipment; 2) 22% handle vehicle traffic volumes greater than 5000 vehicles/day; 3) 29% handle more than 10 trains/day; 4) 40% have a road speed of more than 60 km/h; 5) 20% have a train speed of more than 60 mph; 6) 21% have more than one track; and 7) 14% have more than two lanes. Targeting these features from the given analysis can help reduce the accidents at HRGCs in cluster-1.

Recommendations

The ML algorithms highlight how railway, highway, environmental, and human factors contribute to HRGC accidents and the severity of associated casualties. Important railway and road factors discussed above include maximum train speed, number of tracks, daily train volumes, number of lanes, maximum road speed, and traffic volume. Environmental factors such as season, hour of the day, and visibility also contribute to HRGC accidents and consequences. Human factors include intentional attempts to cross, distracted/confused drivers, visibility obstructions, fatigue, slip of memory/attention, cognitive and emotional distractions, etc. (Baysari et al., 2008; Sekasi & Solihu, 2021).

Based on the results of this study, possible strategies to reduce HRGC accidents and related casualties are as follows:

1. Installing gates and automatic railway-controlled crossings can restrict vehicles from entering the tracks (Report on Railway Safety and Interoperability in the EU - 2022, 2022). Upgrading passive crossings to active crossings by installing flashing lights, bells, and gates can help to reduce HRGC accidents (Mok & Savage, 2005). Additionally, installing four-quadrant and median barriers reduce the chances of accidents at HRGCs and reduce

severity in case of crashes (Dezhkam & Eslami, 2021). Table 8 shows the effects of crossing features on HRGC accidents and the severity of casualties.

Table 8. Effect of crossing features on crossing accidents and fatalities (Chadwick et al., 2014)

No.	Crossing feature	Effect
1	Flashing lights	1. Reduction by 64% in HRGC crash accidents in contrast to HRGCs with only crossbucks.
		2. Reduction in injuries by 84% and reduction in fatalities by 83% when compared with only crossbucks.
2	Lights and gates (2) with flashing lights	1. Reduction by 88% in HRGC crash accidents compared to HRGCs with only crossbucks.
		2. Reduction in injuries by 93% and reduction in fatalities by 100% when compared with only crossbucks.
		3. Reduction by 44% in HRGC crash accidents compared to HRGCs with flashing lights.
3	Median barrier	Reduction by 80% in violations compared to 2-gate system.
4	Long arm gates (3/4 of road coverage)	Reduction by 67 to 84% in violations compared to 2-gate system.
5	4-quadrant gate system	Reduction in violations by 82% compared to 2-gate system.
6	4-quadrant gate system + median barriers	Reduction in violations by 92% compared to 2-gate system.

2. The development of grade separations for crossings that handle high daily vehicle and train traffic is a good solution to reduce the risk of crashes between trains and vehicles (Blagojevi et al., 2021). Grade separation showed a 100% decrease in injuries and fatalities (Chadwick et al., 2014).

3. Advanced warning devices can be implemented to address the effects of a large number of highway lanes and tracks at HRGCs (Keramati et al., 2020). Chadwick et al. (2014) recommend an automated photo and video enforcement system to help investigate vehicle users' compliance with existing warning infrastructure at HRGCs. This system has reduced HRGC-related violations by 34-94%.

4. Reduction of train and vehicle speeds during their approach to high-risk crossings can reduce HRGC accidents and the severity of associated casualties (T. et al., 2011).

5. Reduced lighting and/or hindrance to recognizing the incoming train are factors in HRGC accidents. Thus, installing a lighting source and clearing obstructions from the nearby area could reduce the risk of HRGC crashes (Blagojevi et al., 2021). Provision of lighting sources at HRGCs resulted in a reduction of nighttime accidents by 52% (Chadwick et al., 2014).

6. Pavement strips/rumble strips near crossings are noticeable and effective features in helping drivers recognize upcoming crossings (Tey et al., 2013).

7. Education through campaigns, for drivers and pedestrians, about traffic discipline and the consequences of HRGCs crashes to individuals and railway can be effective (Sekasi & Solihu, 2021). Awareness campaigns have resulted in a 15% reduction in HRGC accidents and a 19% reduction in fatalities associated with HRGC accidents (Chadwick et al., 2014).

Conclusion

HRGCs are regarded as high-risk areas on railway networks because of the catastrophic consequences that can result from HRGC accidents. Thus, transportation authorities place a great focus on safety at HRGCs. This study identified the major causal factors for HRGC accidents, and the severity of casualties associated with HRGC accidents in Canada. The results indicate high train traffic, high vehicle traffic, high highway speed, and high track speed are major factors that contribute to HRGC accidents, while occurrence hour, type of vehicle, high train traffic, high vehicle traffic, high highway speed, and high train speed are major factors that contribute to the severity of casualties associated with HRGC accidents. The ML models help predict HRGC accidents and the associated severity of casualties by employing supervised ML algorithms. These supervised ML models are handy tools for authorities to interpret the data and re-apply using updated data whenever required in the future. The causes identified in this research are matching with the study identified in the introduction section. In addition, optimized hotspot analysis using ArcGIS software recognized the spatial patterns of HRGC accidents in Canada's rail network. Identifying such HRGC accident hotspot locations will allow authorities to target high-risk accident-prone areas of the railway network.

The findings of this research can benefit authorities and policymakers with respect to decision-making, allocating resources, and implementing countermeasures to reduce the number of HRGC accidents and the severity of associated casualties in Canada's rail network. However, this study is not without limitations. The source datasets used for this research had many empty features due to poor reporting, which were thus excluded from the datasets used in the analysis. As such, the analysis may not have identified all causal factors for HRGC accidents and the severity of associated casualties. Furthermore, the classification model datasets did not consider human-related features such as driver experience and state (physical/mental) and gender. Thus, future research should investigate the role of human factors in HRGC accidents and the severity of associated casualties to provide more insight and help improve the safety of HRGCs in the rail network.

Chapter 3: Risk Assessment of the Train Inspection Portal System (TIPS) using a Machine Learning-Fuzzy-Failure Mode and Effect Analysis (Fuzzy-FMEA) Technique

Abstract

New technologies are being developed worldwide to improve decision-making, reduce errors, lower costs, and save time while ensuring integrity, safety, and reliability are not compromised. The train inspection portal system (TIPS) is one such technology currently used for the remote inspection of railcars. Conducting reliability and risk assessments of this technology at the early stage is very helpful in identifying and rectifying potential issues that will affect the technology at later stages of implementation. Failure mode and effect analysis (FMEA) is one of the most promising techniques for risk assessment, identifying potential system failures as well as their impacts and repercussions. Although FMEA is widely used in many industries, the approach does have some limitations. To overcome the challenges for FMEA and identify the important potential failures for the TIPS, this study used a fuzzy failure mode and effect analysis (fuzzy-FMEA) as a machine learning approach for better decision-making considering the vagueness and imprecision of real-life language. This study used a 5-point scale to determine rankings for severity, occurrence, and detectability. Ultimately, recommendations are made for addressing the high-risk priority number (RPN) failure modes for which implementation in the field would significantly reduce the risk of failure and enhance the system's overall reliability.

Keywords: Fuzzy-FMEA, Fuzzy-RPN, TIPS, Triangular fuzzy number, Reliability

Introduction

Advancements in technology have revolutionized various industries, including manufacturing, communication, healthcare, education, and transportation, among others. These technologies are helping humans with better decision-making, reducing mistakes, lowering costs, and saving time. The reliability of any technology or system depends upon its various subsystems, components, and equipment. The reliability of a component is the likelihood that the component will work satisfactorily for at least a specific period when employed under specific conditions (Johansson et al., 2013). Thus, a crucial concern during the initial phase of system design is the reliability of the entire system and limiting the required downtime (Afolalu et al., 2018). Conducting an early risk assessment of technology can help identify potential issues and implement preventative measures. Failing to do so can result in significant costs during later stages of development. The failure mode and effect analysis (FMEA) technique is widely used to improve an overall system's reliability (Huang et al., 2020). This systematic risk assessment technique uses historical failure data to evaluate and reduce the risk of failures of design, processes, and services (Liang & Li, 2021).

FMEA was first developed by the United States (US) military in 1940 and used as a semi-quantitative risk assessment method (Akbari et al., 2013). Since then, FMEA has been widely employed as a promising technique for ensuring safety and reliability in the nuclear, aerospace, automotive, chemical, mechanical, and electronics industries (Huang et al., 2020; Nuchpho et al., 2014). FMEA is a suitable method for assessing design reliability by considering the causes and effects of failure modes in a complex system (Balaraju et al., 2019). It is a systematic team approach that identifies and examines the possible failure mode of a system or product or process, and gives its possible adverse outcomes. It also provides recommendations that could reduce or nullify the chance of system failure. Conventional FMEA is based on three factors: severity (S), occurrence (O), and detectability (D). FMEA uses a risk priority number (RPN) calculated by multiplying rankings of the S, O, and D factors (Eq. 10) (Nasruddin et al., 2018):

$$\text{RPN} = \text{S (Severity)} \times \text{O (Occurrence)} \times \text{D (Detectability)}. \tag{10}$$

Many studies have been conducted in various sectors, such as manufacturing, healthcare, and product design, using the conventional FMEA method. These FMEA studies were conducted using different ranking schemes, such as the 10- and 5-point schemes for S, O, and D ranking. Goel and Graves (2007) conducted an FMEA study for increasing reliability in the electronic system production industry using a 10-point scale; these authors stated FMEA was a simple method for evaluating the reliability of complex electronic systems that identified 48 potential failure modes. Lago et al. (2012) used the FMEA technique to reduce the hazards associated with drug delivery to children at Padua University Hospital in Italy. Five multidisciplinary teams conducted this study, and high-risk failure modes (RPN>48) were treated with risk-reduction strategies. A group of researchers from China used the FMEA technique for product development in a nuclear plant facility; their study implemented a 10-point scale for conducting FMEA on reheat valve design that helped enhance the product's stability at an early stage (Wu et al., 2012). Feili et al. (2013) conducted an FMEA study for geothermal power plants (GPP) in Iran to reduce potential failures. Experts from five different organizations were involved in the study to collect the S, O, and D rankings for various failure modes, with overhauling/replacing equipment, regular maintenance/calibration, conducting root cause analysis and redesigning the system offered as mitigative strategies. Another risk management study conducted by Ebrahemzadih et al. (2014) for an Iranian steel company used the FMEA technique and a 10-point scale. The study identified 17 failure modes for the steel processing complex and the high-risk failure modes using the RPN. The authors provided corrective actions for high-risk modes, and a reassessment of failure modes after implementing these actions showed a reduction in RPNs. Thakore et al. (2015) used a 10-point scale and the FMEA technique to enhance the quality and efficiency of the bearing manufacturing process in India. These authors identified seven failure modes, and the output of the FMEA identified the ranking of the failure modes based on the RPN. This study helped prioritize the most critical causes of failure in the manufacturing process. Martin et al. (2017) used an FMEA study with a 5-point ranking scheme at Seattle Children's Hospital, US, to reduce medication errors in pediatric anesthesia. The study identified eight high-risk failure modes and resulted in the implementation of countermeasures that helped reduce the median medication error rate from 1.56 to 0.95 per 1000 anesthetics. To reduce the errors in dispensing medicines in pharmacies and improve patient safety, Stojković et al. (2017) used an FMEA study with a 5-point ranking scheme in Germany. The analysis was conducted by a ten-member team that identified 30 failure modes for the medicine dispensing process and found the top 14 failure modes of the high-risk category with RPN values greater than 12. The outcomes of the analysis aided in the implementation of corrective actions and led to a reduction in risk for most high-risk failure modes.

Although conventional FMEA helps lower the risk of system failure and enhances safety and reliability, it still has a few drawbacks. Conventional FMEA gives equal weights to rankings of S, O, and D for RPN calculations, and thus returns the same RPN for different combinations of S, O, and D using Eq. (10). As such, the value of the RPN cannot be used to define the order of corrective action for mitigation (Liu et al., 2013). For example, in the RPN calculation, a failure mode with very high severity, low rate of occurrence, and very high detectability (say S = 9, O = 3, and D = 2) may have a lower RPN at 54 than one with all parameters moderate (say S = 4, O = 5, and D = 6) that has an RPN of 120. In this case, the criticality of the former failure mode is high compared to the latter due to its high severity ranking, yet the RPN value is equally high for the latter, arguably less critical situation. Also, precise value estimation for S, O, and D ranking is difficult. In practical applications, the criteria used to evaluate the three risk factors are often expressed in natural language, leading to imprecision, ambiguity, and vagueness when using conventional FMEA. RPNs are scattered over the range of 0 to 1000 (for a 10-point scheme) and 0 to 125 (for a 5-point scheme) and are distinct values and not continuous in nature.

To overcome the shortcomings of conventional FMEA and incorporate the vagueness of real-life systems, an advanced technique known as fuzzy-FMEA was developed (Zúñiga et al., 2019). In this approach, the three hazard variables S, O, and D are described based on fuzzy linguistic terms, and risk is evaluated by applying fuzzy system fundamentals. Fuzzy logic works on natural language, mostly used in normal life. Subject matter experts can build such models requiring no additional training. The mathematical concepts of fuzzy interface systems are relatively straightforward. A fuzzy logic system is adaptable and can accept data inaccuracies in the datasets. Complex non-linear models can also be handled accurately and efficiently (Balaraju et al., 2019).

Fuzzy-FMEA is used in various industries, including the oil and gas industry and medical industry, and for the maintenance of technical systems in mining and shipping (Łapczyńska & Burduk, 2021). Sharma et al. (2005) conducted a failure risk assessment of a hydraulic system using the fuzzy-FMEA technique in India. The study's findings support the conclusion that the fuzzy logic-based approach not only overcomes the drawbacks of traditional RPN evaluation methodology but also enables experts to provide a more flexible and realistic way of using their knowledge, experience, and expertise. A Romania-based group of researchers compared FMEA and fuzzy-FMEA for failure risk evaluation of injection pumps (Rachieru et al., 2014). A risk assessment study in medical product development performed using a traditional FMEA and fuzzy-FMEA approach in India found the fuzzy-FMEA approach produces more exact, appropriate, and logical conclusions than traditional FMEA (Kirkire et al., 2015). The study results demonstrate that applying the fuzzy-FMEA method can lead to a reasonable ranking and help the FMEA team more accurately assess and rank risks. Ivančan & Lisjak (2021) conducted a reliability evaluation study for various equipment in an oil refinery in Croatia. The study used fuzzy logic for severity, occurrence, and detectability and found the fuzzy-RPN for various failure modes. The outputs increased the quantification of failure mode risk accuracy and the prioritization of mitigation efforts. Overall, the fuzzy-FMEA approach is more accurate than conventional FMEA and reduces the likelihood of producing comparable RPN values with different consequences (Rahimdel & Ghodrati, 2021; Sifwat et al., 2021). The estimated fuzzy-RPN could be used to better prioritize mitigation measures/recommendations to identify all high risks.

This study focused on performing a risk assessment of the train inspection portal system (TIPS) system using fuzzy-FMEA method. TIPS is a semi-automated machine vision technology used to remotely inspect railcars in trains and identify different railcar defects using images captured by a camera system. The camera system captures 360° images of railcars, which are then inspected by remote certified car inspectors (CCIs) and flags any defects/potential defects in the railcars of the trains. This system consists of equipment including automatic equipment identification (AEI) tag readers, cameras, cloud servers, blowers, heaters, air conditioning units, etc. Ensuring the reliability of the system is crucial for conducting remote railcar inspection, and this reliability depends on various pieces of equipment. To the best of the authors' knowledge, limited research has been conducted on remote railcar inspection technology in the railway industry. Therefore, we conducted a risk assessment during the early design stages of TIPS technology implementation to identify potential risks and implement appropriate mitigative measures. The main objectives of this research were to i) conduct a risk assessment of TIPS using the fuzzy-FMEA method and ii) identify the ranking of various failure modes and provide recommendations to improve the reliability of this technology.

Methodology

This research developed a fuzzy-FMEA based on fuzzy logic theory and the conventional FMEA method. The advantage of fuzzy theory application for risk assessment is that the resulting system assessment is qualitative and can operate with linguistic variables as some events cannot be described numerically. The fuzzy sets overcome two significant complications related to modelling with mathematical language (Zimmermann, 2001): first, real-life circumstances are rarely straightforward and deterministic and thus difficult to define precisely; and second, a comprehensive description of a genuine system frequently necessitates far more specific data than a human could ever identify, interpret, and comprehend. The fuzzy logic methodology comprises four steps: fuzzification, if-then rule base, fuzzy inference system, and defuzzification (Figure 20).

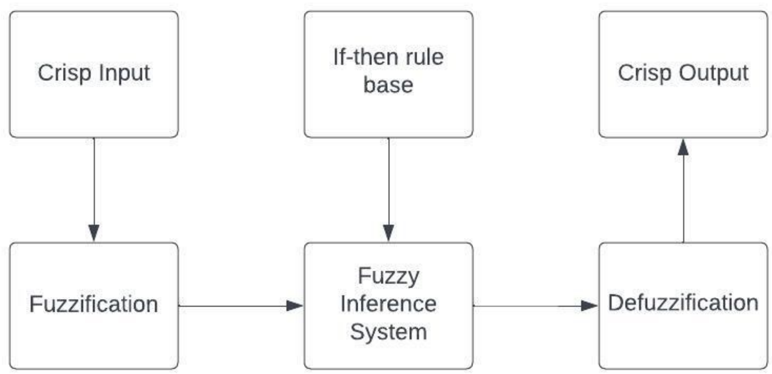


Figure 20. Flow chart for fuzzy logic methodology

Fuzzification

Fuzzification refers to the conversion of crisp input data into a fuzzy input set using membership functions and linguistic terms (*Fuzzy Logic Fundamentals*, 2001). A membership function (MF) is a curve that specifies how each point in the input space is mapped to a degree of membership that ranges from 0 to 1. The MF is a building block for fuzzy set theory, which is used to determine the fuzziness of the system. MFs have a shape that is chosen by the individual based on experience, such as triangular, trapezoidal, Gaussian, or π-shaped (Adil et al., 2015). All MFs should have a unique degree of membership for all values of the set. The shape of MFs is determined by one's beliefs about a particular linguistic variable. Deciding the number of MFs and distribution of intervals is equally important as the shape of the MF (*Fuzzy Logic Fundamentals*, 2001).

The number of MFs and their shapes influence the computational time in solving fuzzy logic problems. Princy & Dhenakaran (2016) compare fuzzy controller performance using three different MFs; the triangular and trapezoidal MFs both performed better than the Gaussian MF, but the results of the fuzzy output in terms of memory usage and arithmetic operations clearly indicated the triangular MF consumed less computer memory than the trapezoidal MF.

The triangular MF is a widely used MF for solving problems with a fuzzy approach. Triangular MFs can be defined with three parameters, a, b, and c, as shown in Figure 21. The (a, b, c) is defined as a triangular fuzzy number (TFN). The degree of membership μ can be calculated using Eq. (11), where x is any point on the x-axis:

$$\mu_{Triangular}\,(x; a, b, c) = max\,\left(min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right). \tag{11}$$

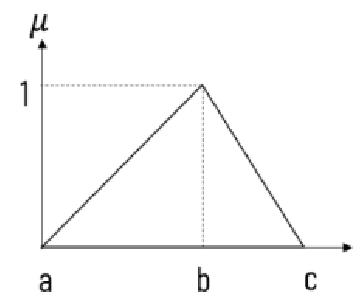


Figure 21. Triangular fuzzy MF

If-then rule base

After deciding on the MFs of the fuzzy system, the next step is to decide the if-then rule base. The if-then rule base is a set of fuzzy rules used to identify the relationship between input and output variables. Developing fuzzy rules requires a high level of system knowledge and sufficient experience with the system (Tay & Lim, 2006). A single-variable fuzzy rule is defined as "if x is A, then y is B", where "x is A" is the antecedent and "y is B" is the consequent. When more than one variable is available in the system, different logic operators are used in the antecedent to develop a fuzzy rule (Xu et al., 2002). Logical operators (e.g., intersection, union, and complementation; Figure 22) are used to develop fuzzy system rules. A rule's output is shaped by the firing strength, which is the outcome of the operators used in defining the rules (Dernoncourt, 2013).

The intersect operator (also known as t-Norm) finds the common elements of the two fuzzy sets and retains the lowest membership value if an element is available in both sets. Thus, the intersect operator finds the lowest degree of MF for elements (Eq. 12). For example, consider two sets, A and B, in the universe of U. The intersect operator is denoted as A ∩ B (Popescu & Pistol, 2021):

$$\mu_{A \cap B} = \min[\mu_A(x), \mu_B(x)]. \tag{12}$$

The union operator (s-Norm) connects the two sets together to create a new set. The union operator considers the element value only once and takes the highest value of the MF for elements. Thus, the union operator finds the maximum degree of membership for given elements (Eq. 13). For example, consider two sets A and B in the universe of U. The union operator is denoted as A U B (Popescu & Pistol, 2021):

$$\mu_{A \cup B} = \max[\mu_A(x), \mu_B(x)]. \tag{13}$$

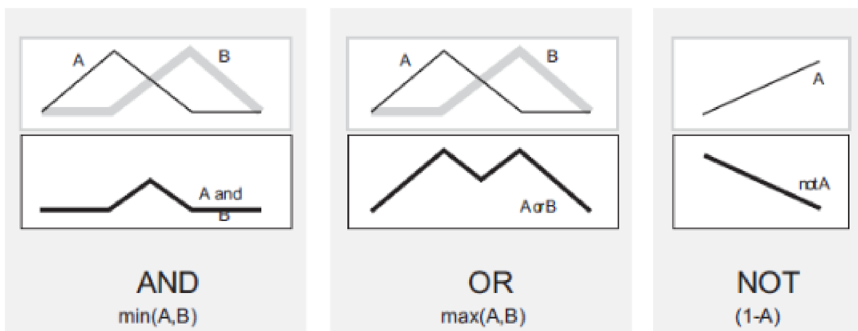


Figure 22. Types of fuzzy logic operators (Wang, 2015).

The complement operator behaves opposite to the degree of membership (Eq. 14). For example, consider a set A in the universe of U. The complement of A is denoted as Ā (Popescu & Pistol, 2021):

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x). \tag{14}$$

The two most widely used fuzzy rule-based models in the fuzzy logic system are the Mamdani model and Takagi-Sugeno-Kang (TSK) model (Kumru & Kumru, 2013). The present study employs the Mamdani model, which uses linguistic variables in the antecedent and consequent for establishing a fuzzy rule-based system. Mamdani's model is highly efficient for linguistic inputs by humans (Riza et al., 2019). The Mamdani system features two types of if-then rules (Khosravanian et al., 2016): multiple input and single output (MISO) and multiple input and multiple-output (MIMO). An example of MISO would be as follows: if X_1 is A_1 and . . . and X_n is A_n, then Y is B. Here, X_n and Y are linguistic variables and A_1,…, and A_n and B are linguistic terms of respective variables (Ding et al., 2000).

Fuzzy rules calculate the system's output based on different linguistic terms used in the input and fuzzy operators employed in individual rules. Defining the fuzzy rules by if-then structure is important for obtaining the fuzzy output. For any given system, the number of fuzzy rules can be calculated using Eq. (15):

$$\text{Number of fuzzy rules} = m^n, \quad (15)$$

where m is the number of MFs in variables and n is the number of input variables in the system (Geramian et al., 2019).

Fuzzy inference system

The fuzzy inference system obtains fuzzy output from fuzzy input sets by applying different fuzzy rules defined in the rule base (Rizvi et al., 2020). The fuzzy inference system determines the number of antecedents of rules that apply to a given fuzzy input set. More than one rule may be satisfied for a given fuzzy input. The fuzzy rules are fired in parallel with the inference system and rule base to obtain a fuzzy output set (Fuzzy Logic Fundamentals, 2001). The results of every rule are then combined, which is called aggregation. The final fuzzy set represents each rule's output integrated into a single fuzzy set as the aggregation of multiple rules.

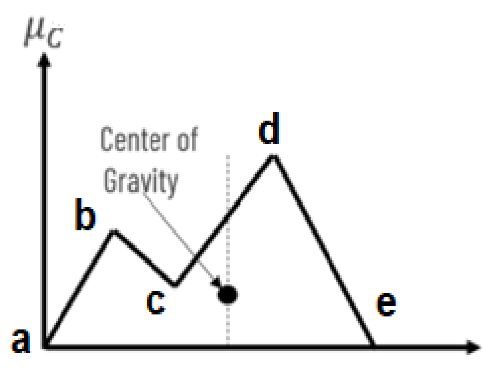


Figure 23. Center of gravity method for defuzzification (Center of Gravity (CoG) Method for Defuzzification, 2023)

Defuzzification

Defuzzification processes the output fuzzy set to obtain a crisp output value. The fuzzy output set from the fuzzy inference system is obtained in the form of G_i (i=a, b, c, d, e) on the output MF (Figure 23), where a, b, c, d, and e represent the value on the MF (Rizvi et al., 2020). Many methods are available to give a crisp output from a fuzzy output set, such as centroid, maximum membership method, mean of maxima method, weighted average method, etc. (Defuzz: Defuzzify Membership Function, 2023). The most widely used defuzzifier is the centroid method (also known as the center of gravity), which gives a crisp value based on the center of gravity of the aggregated fuzzy output set using Eq. (16) (Kumru & Kumru, 2013):

$$\boldsymbol{Z} = \frac{\sum_{j=1}^{n} Z_j * \mu_c (Z_j)}{\sum_{j=1}^{n} \mu_c (Z_j)}, \tag{16}$$

where μ_c represents the fuzzy membership set, Z_j is the value of the membership, and Z is the crisp output of the fuzzy system. The center of gravity method was used in our research as the defuzzification method (Sharma et al., 2005).

Proposed Framework for Fuzzy-FMEA

For the fuzzy-FMEA, failure is defined as the inability of TIPS "to perform its intended function" (Abdelgawad & Fayek, 2010). In this fuzzy-FMEA study of TIPS, we defined the linguistic terms and triangular MFs for three input variables (S, O, and D) and one output variable (fuzzy-RPN) as a part of the fuzzy system. MATLAB R2021a software was used to develop the fuzzy-FMEA machine learning code. The fuzzy-FMEA was conducted using an FMEA sheet containing various elements, including item/function, failure mode, potential failure cause, severity, potential failure effect, occurrence, current design control, detectability, fuzzy rule base for fuzzy-FMEA, and fuzzy-RPN (Ivančan & Lisjak, 2021).

Item/function

An item/function is the system/process or section of the system/process on which the team performs FMEA.

Failure mode

Failure mode refers to how the product or process could fall short of fulfilling its intended purpose and any necessary conditions. It may also involve executing an unwanted or undesirable function, performing a function insufficiently, poorly, or intermittently, or failing to complete a task.

Potential failure cause

Potential failure cause is the precise reason for the failure of an item/function, ideally discovered by repeatedly asking "why" until the underlying cause is identified.

Severity

The severity is the ranking given to the failure mode based on its worst possible effect. Table 9 shows the crisp severity ranking for FMEA on a scale of 1 to 5, with 1 being the least severe effect and 5 being the highest severe effect of the failure mode on the system (J. Singh et al., 2020). The experts assess the severity of effects caused and give a crisp severity ranking to the failure mode of the item/function from Table 9.

Table 9. Severity ranking table (Modified from Chin et al., 2009).

Severity ranking	Severity
1	No effect on TIPS.
2	TIPS is operable with a minor reduction in the quality of TIPS images.
3	TIPS operable with a moderate reduction in the quality of TIPS images.
4	TIPS is operable, but a major reduction in the quality of TIPS images and inspection is very difficult.
5	TIPS is inoperable, and no images are captured or no image access on the remote server.

Three linguistic terms (low, medium, and high) were defined for the severity variable for the fuzzy-FMEA technique. The TFNs were used to map the linguistic terms over the universe of discourse (U of D) [0,5], which is defined as the set of potential values that can be allocated to the variable. Hence, three MFs were used to define the severity variable over the U of D (Table 10). Figure 24 shows the MFs generated using TFNs for the severity variable.

Table 10. TFNs and linguistic terms for severity (Modified from Balaraju et al., 2019).

TFN	**Linguistic term**	**Meaning**
0-0-2.5	Low	System operable with relatively less severe failures.
0-2.5-5	Medium	System operable with relatively moderate failures.
2.5-5-5	High	System inoperable due to destructive/harsh failure.

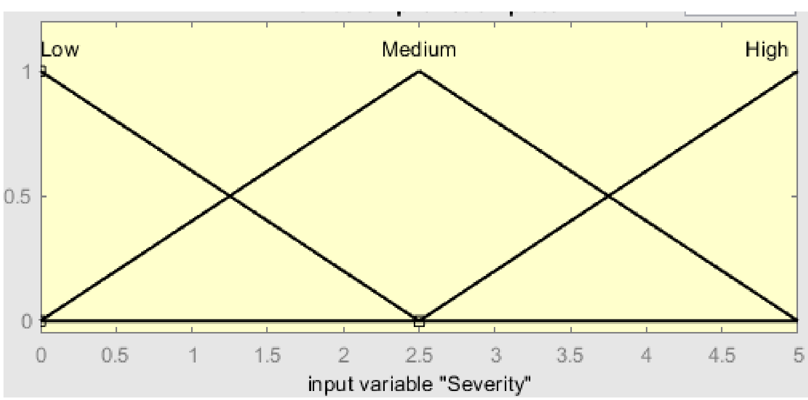


Figure 24. MFs for severity

Potential failure effect

The potential failure effect is the result of a failure mode for the system or process. All possible potential worst effects of failure modes are noted on the FMEA sheet.

Occurrence

Occurrence is the likelihood/probability of an identified cause happening during the life cycle of the item/function. The occurrence ranking is calculated based on the mean time between failures

(MTBF). Table 11 shows the crisp occurrence ranking for conventional FMEA, where 1 represents the least likelihood, and 5 represents the highest likelihood of occurrence (J. Singh et al., 2020). Experts provide the crisp ranking for occurrence from Table 11, based on MTBF data from the previously published incident report and experience of different failures.

Table 11. Occurrence ranking table (Modified from Sharma et al., 2005).

Occurrence ranking	**MTBF (Mean Time Between Failure)**
1	>3 years
2	1-3 years
3	6 months – 1 year
4	3-6 months
5	<3 month

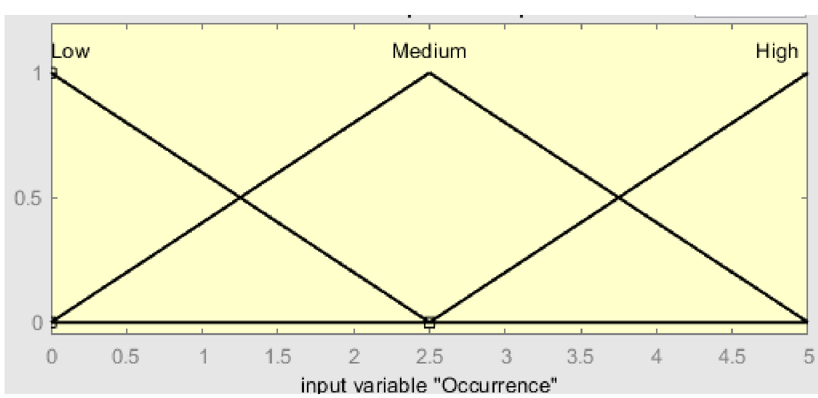


Figure 25. MFs for occurrence

Similar to the severity variable, three linguistic terms (low, moderate, and high) were defined for the occurrence variable, with the TFNs used to map the linguistic terms over the U of D [0,5]. Hence, three MFs were used to define the occurrence variable over the U of D (Table 12). Figure 25 shows the MFs generated using TFNs for the occurrence variable.

Table 12. TFNs and linguistic terms for occurrence (Modified from Sharma et al., 2005)

TFN	Linguistic term	Meaning
0-0-2.5	Low	Cause has a low frequency of occurrence.
0-2.5-5	Medium	Cause has an occasional frequency of occurrence.
2.5-5-5	High	Cause has a repeated frequency of occurrence.

Current design control

Current design controls are the strategies or measures currently being considered available to lessen or eliminate the risk related to each potential cause. Control measures can be used to stop or identify the cause during the product development process or activities taken to identify an issue during service before it becomes catastrophic.

Detectability

Detectability ranking refers to current design control for how effectively it detects the failure occurrence. The FMEA team uses the lowest ranking of detectability when accessing more than one design control. Table 13 shows the crisp detectability ranking in which 1 indicates when design control can undoubtedly detect the problem, and 5 indicates when no design control is available for failure mode (J. Singh et al., 2020).

Table 13. Detectability ranking table (Modified from Chin et al., 2009).

Detectability ranking	Detectability	Description
1	Controls will almost certainly detect the problem of the system.	Detected 9/10 times

2	Design control will be sufficient for detecting a problem.	Detected 7/10 times
3	Design control has a moderate chance of detecting a problem.	Detected 5/10 times
4	Design control will be insufficient for detecting a problem.	Detected 2/10 times
5	Control will not and/or cannot detect a problem, or there is no design control.	Detected 0/10 times

Again, three linguistic terms (low, moderate, and high) were defined for the detectability variable. The TFNs were used to map the linguistic terms with the U of D of [0,5]. Hence, three MFs were used to define the detectability variable over the U of D (Table 14). Figure 26 shows the MFs generated using TFNs for the detectability variable.

Table 14. TFNs and linguistic terms for detectability (Modified from Sharma et al., 2005)

TFN	**Linguistic term**	**Meaning**
0-0-2.5	Likely	High probability of detection.
0-2.5-5	Medium	Moderate probability of detection.
2.5-5-5	Unlikely	Low probability of controls to detection.

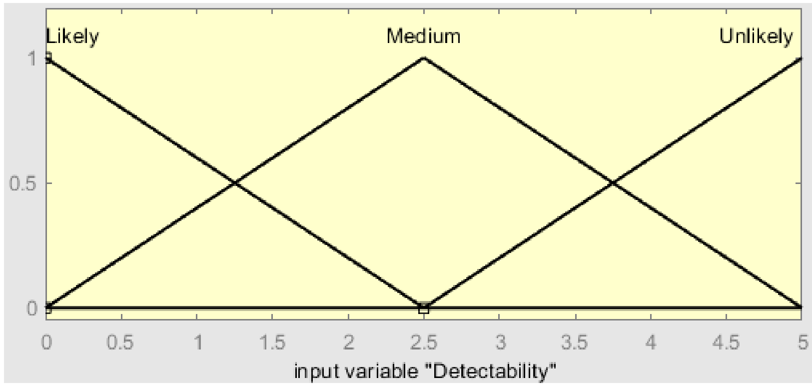


Figure 26. MFs for detectability

Fuzzy rule base for fuzzy-FMEA

In this research, the S, O, and D variables each have three MFs. Thus, 27 ($m^n=3^3$) rules were required for the fuzzy-FMEA system. The fuzzy logical operator AND was used for the fuzzy system as S, O, and D are dependent on each other to generate output variables (fuzzy-RPN). The Mamdani model was used to define fuzzy rules in a fuzzy rule base, as it is highly efficient with human reasoning modelling (Rizvi et al., 2020). The fuzzy rules were developed with expert knowledge; all rules are available in Appendix 3. Fuzzy output is generated based on the fuzzy inference system by using the fuzzy rule base and fuzzy inputs.

Fuzzy-RPN

The output of the fuzzy inference system is the fuzzy output that was defuzzified using the center of gravity method. The final crisp output shows the crisp output value of the fuzzy-RPN for comparison of failure modes of the system.

Three linguistic terms (low, medium, and high) were defined for the fuzzy-RPN output variable (Table 15). TFNs were used to map the linguistic terms with the U of D of [0,125]. Hence, three membership functions were used to define the fuzzy-RPN variable over the U of D (Table 15). Figure 27 shows the MFs generated using TFNs for the fuzzy-RPN variable.

Table 15. TFNs and linguistic terms for RPN

TFN	Linguistic term
0-0-62.5	Low fuzzy-RPN

0-62.5-125	Medium fuzzy-RPN
62.5-125-125	High fuzzy-RPN

Fuzzy-RPNs give an idea about the risk associated with each individual failure mode. A higher fuzzy-RPN indicates higher risk is associated with the failure mode (Yucesan et al., 2021). The range of fuzzy-RPNs is between 0 and 125. To implement mitigative measures for the system, high-risk failure causes must be found and identified. In this study, we used a measure of 66.67% of the range value (66.67% × 125 = 83.33) as a threshold (Farhanah, 2020). Thus, a failure cause with a fuzzy-RPN value greater than 83.33 is considered a high-risk failure cause.

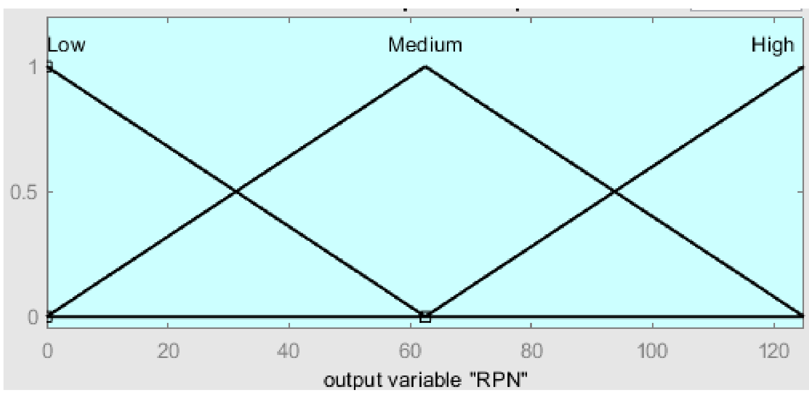


Figure 27. MFs for fuzzy-RPN

Fuzzy-FMEA Applied to TIPS

This study is part of the automated machine vision inspection system (AMVIS) project and was conducted as a team effort involving experts in portal office inspection (POI) technology, some from a renowned railway company and others affiliated with a prominent research and development organization. The ranking scores required for different failure modes were determined based on opinions from the experts. Their knowledge helped to provide rankings of the three factors (S, O and D) that were used to conduct this risk assessment of POI technology.

We classified the system into various subsystems to analyze the TIPS technology's failures and fully understand all failure modes. TIPS is comprised of three subsystems. First, the AEI tag system is used to identify the railcar ID by TIPS software to assign the camera images. This system comprises the wheel detector electronics and cables connected from the trackside to bungalow equipment. Based on the AEI data, the photos and data are matched to specific cars, making the car parts available for inspection and study. Second, TIPS has four camera systems — CSCView, AHView, TruckView, and TrainView that function to capture images of the railcar when it passes through the TIPS portal. The cameras are located around the tracks using structures called the gantry. Five cameras are installed in the bottom tie of the rail to inspect the railcar's undercarriage. Combined, these camera systems capture 360° views of railcars. Third, TIPS has a bungalow structure that houses various equipment that is part of the system. This includes: i) two air conditioning units to maintain the temperature inside the bungalow, which is required for working system computers and server units; ii) a communication system to transfer the images captured by camera units to cloud servers. Remote CCIs can use the images on the servers to inspect the railcars. Data are transferred over the local area network (LAN), and Trimble (the company that developed the inspection technology) can access the system remotely for system management and diagnosis; iii) power distribution units supply power to trackside equipment. The power lines are protected against power surges using circuit breakers. The power and connection cables from trackside equipment are connected to different systems inside the bungalow. These cables are connected using underground conduits; iv) a heater/blower system to blow snow from the CSCView cameras. This system activates based on the environmental conditions of the site location. The AEI tag reader activates the system before the train passes through the TIPS portal; and (v) servers to transfer the images captured by the TIPS camera system to the company-owned server. Through the WISE server, these images are available to the Train Watch software that is used for the inspection of railcars for any type of defects.

Procedure for fuzzy-FMEA

The steps followed for the fuzzy-FMEA of TIPS technology are as follows: 1) a subsystem or component of the system is selected for fuzzy FMEA; 2) different failure modes or potential failure modes are identified for the subsystem/ component of step 1, and experts recognize failure modes based on their experience with subsystems/components; 3) experts identify the potential failure effects for the failure mode selected in step 2; 4) using the experts' knowledge and experience, the crisp severity ranking of the identified failure effect is selected from Table 9; 5) using the expertise of POI technology experts, potential failure causes are identified for the failure effects found in step 3; 6) the crisp occurrence ranking of the identified failure causes is chosen from Table 11 using the experts' expertise; 7) current design controls for the potential failure cause, if any, available in the system are identified; 8) the crisp detectability rankings for identified current design controls are chosen from Table 13 using the experts' expertise; 9) all crisp rankings of severity, occurrence, and detectability are input in MATLAB code, and the crisp input is processed into a crisp output based on the MFs of fuzzification, fuzzy rules, and defuzzification methods; 10) output is obtained as a fuzzy-RPN from the MATLAB code for fuzzy-FMEA; 11) after analysis of all failures/potential failures of subsystems/components, failure modes are ranked according to descending order of fuzzy-RPNs; and 12) high-risk failure modes are identified according to fuzzy-RPN values, and recommendations provided to reduce the risk of POI technology failure and improve reliability. Figure 28 is a flowchart of these steps for the fuzzy-FMEA applied to TIPS technology.

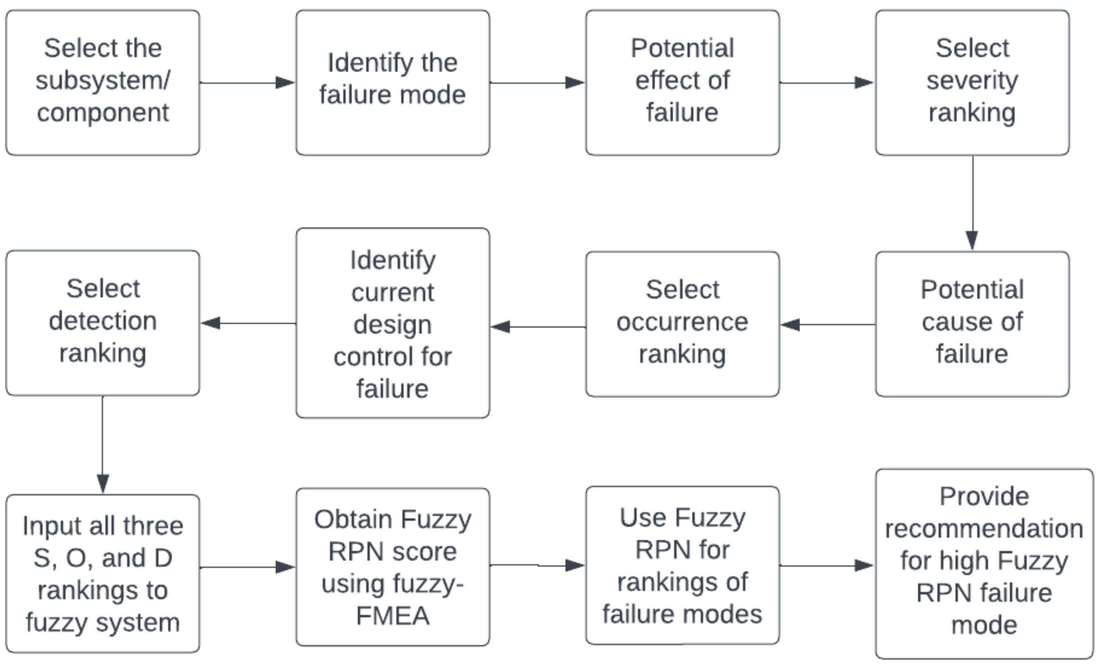


Figure 28. Steps for fuzzy-FMEA

Results

The fuzzy-FMEA study of TIPS allowed us to conduct a systematic analysis to identify failure modes and their effects on the performance of TIPS in its entirety.

The team followed the procedure outlined above and identified 16 failure modes that led to potentially 29 failure causes for TIPS. The experts unanimously decided on severity, occurrence, and detectability rankings based on their experience and previous troubleshooting issues/problems.

Finally, fuzzy-RPN values were calculated using the developed MATLAB code. Appendix 4 outlines the results of this process.

A comparison of all failure causes shows a total of 16 causes had fuzzy-RPNs greater than 83.33; these were identified as high-risk failure causes that strongly affect TIPS operation and reliability (Table 16). These high-risk failure causes were associated with the AEI tag reader, camera, cable, power supply, bungalow, heater/blower, and algorithm/software issues. The potential failure modes for TIPS were a malfunction of items, full/partial power failure, software issues, damaged power cables, AEI tag circuit failure, and black/no images from cameras. Some other low-risk failure causes (13) have fuzzy-RPN values below 83.33; these causes had less severe effects on TIPS, or their occurrence rate was low, or these failure causes had good detectability.

Table 16. High-risk failure modes of TIPS

No.	Item	Potential Failure mode	Potential effect of failure	Potential causes of failure	Current design control	Fuzzy-RPN
1	Camera	No clear camera images	Full view blocked in images	Banding/blurring/darkening/over-exposure in cameras	Remote CCI performs a visual check for checking full-view blockage in images.	104
2	Power supply	Loss of partial power supply	No images from certain camera view systems	Power distribution unit failure	A notification about any problem is sent to vendor, and then vendor contacts railway organization about problem.	104
3	Algorithm/ Software issue	Beena vision software breakdown (TruckView, CSCView, AHView)	Failure of some camera systems of TIPS (for a few hours to maybe a day)	Software update requirement	Necessary for system update. Railway company tries to plan it beforehand but sometimes affect the remote train inspection.	104
4	Heater / blower	Malfunction of	Full view blocked in	Power failure to heater/blower	Inspection frequency once per two months. No backup for power.	104

		heater/blower	images due to snow			
5	AEI tag reader	Loss of power supply to AEI reader	Failure to sense the presence of the train and failure to start the TIPS	Power supply failure	Auxiliary power using a battery is available for a few hours, and after that no backup supply.	84.5
6	AEI tag reader	Track circuit failure	Failure to sense the presence of the train and failure to start the TIPS	Track condition-shunting	Inspection frequency is one time per year. Remote CCI can check the health of the track circuit by logging into system.	84.5
7	Camera	No clear camera images	Partial view block in images	Banding/blurring/shadowing/over-exposure in cameras	Remote CCI can check by visual check.	84.5
8	Camera	No clear camera images	Partial view block in images	Blowing snow in winter season	Fencing provided on north side of TIPS portal to restrict incoming snow. It is performing well.	84.5
9	Camera	Black images from camera	No image from cameras	Environmental condition dirt & water logging	To avoid water logging, the track is elevated above the ground.	84.5
10	Camera	Black images from camera	No image from cameras	Electric overloading	During the design phase, power requirement for camera system is calculated and sufficient power supply is allocated accordingly.	84.5
11	Cable	Damage to power cable	No image capturing as TIPS is out of power	Insulation damage and continuity loss for cable	Images would not be captured. Failure can be noticed by remote CCI.	84.5

12	Cable	Damage to fibre cable of data transfer	Storage of images on local servers but not able to see on remote server.	Insulation damage and continuity loss for fiber cable	Inspection frequency is 1 time per year. Images can't be accessible, remote CCI can notice a failure to connect and dispatches the technician.	84.5
13	Power supply	Loss of power supply	No power supply & no image of railcars	Power outage in region due to wind blowing/ snow blowing	The external hard wire connection is available on-site to connect electric generator in case of power outage.	84.5
14	Power supply	Loss of power supply	No power supply & no image of railcars	Lighting strike on TIPS equipment	Lightning protection is provided on TIPS equipment.	84.5
15	Heater/blower	Malfunction of heater/blower	Full view blocked in images due to snow	Failure of thermostat	Inspection frequency is one time per year.	84.5
16	Bungalow air conditioner	Malfunction of air conditioner	Bungalow temperature increase with effects on bungalow & internal instruments. Some systems can also go down.	Power failure to air conditioning	Inspection frequency is once in two months. No power backup.	84.5

Recommendations

A comparison of failure modes using fuzzy-RPNs identified the high-risk failure causes for the TIPS technology. Based on the results and the experts' judgment, we recognized 16 high-risk failure causes with fuzzy-RPN values greater than 83.33. Recommendations are provided below for the high-risk causes, so that preventive strategies can be implemented to reduce the risk of system failure and increase the reliable operation of TIPS.

Power supply failure

The fuzzy-RPN results from the fuzzy-FMEA study indicated the failure of the power supply to the AEI tag reader, heater/blower, air conditioning (AC) units, and overall TIPS were high-risk causes. Failure of the AEI tag reader related to the power supply can result in failure to sense the train's presence and failure to start the TIPS. Failure of the power supply to the heater/blower assembly can cause the accumulation of snow on CSCView cameras, which obstructs images from these camera systems. The bungalow houses the TIPS electronic equipment and instruments, all of which can fail due to increased bungalow temperature if the power supply to the bungalow AC fails. Failure of the mainline power supply to TIPS can cause an outage of all TIPS electronics. Thus, the following are recommendations to reduce the effects of power supply failure:

- Provide redundant power sources for TIPS, the heater/blower system, and the bungalow AC, such as electric generators, to sustain system operation in case of a power outage in the region (Miles et al., 2016; Preparing for Power Loss, 2023).
- Develop strategic plans and procedures for responding to and recovering from snowstorms to lower the likelihood of longer power outages and lessen their consequences on TIPS operation (Hou et al., 2009).
- Provide a redundant power supply for the AEI tag reader to ensure system functioning after the battery backup is discharged (Benabid et al., 2019).

Failure due to blurring/over-exposure in cameras

Failure of the camera due to blurring/darkening/over-exposure can result in view blockage in images. Blurring in the images can be caused by low shutter speed and dirt/foreign particles on the lens of a camera, while overexposure can be caused by the heterogeneity of alternating current. Thus, the following are recommendations to reduce such issues:

- Increase the shutter speed of the camera to capture good-quality images without blurring (Ahuja & Barkan, 2007).
- Use a direct current (DC) power source (also called a "stabilized power supply") to reduce power source illumination heterogeneity and help in controlling overexposure problems in images (Jonker et al., 1997).

Failure due to software upgrade

The failure of TIPS can occur due to software upgrades of various camera systems, such as TruckView, CSCView, AHView, and others. These software upgrades are necessary and are typically designed for one camera system at a time. As a result, when a camera system is being upgraded, it will not be available to capture images, and inspection of railcar components through that camera system will not be possible. Following is the recommendation for reducing TIPS failure during software upgrades:

- To minimize any disruption to TIPS during software upgrades, it's essential to plan the update and identify a suitable time slot. Additionally, railway traffic should be managed through the TIPS portal to ensure that TIPS remains operational and can capture images for remote inspection both before and after the software upgrade. This will help ensure that the system remains functional and minimizes any delays in the inspection process.

AEI track circuit failure due to shunting

Failure of AEI track circuit due to shunting causes the failure of detecting the presence of the railcar axle and initiate the image capturing through TIPS camera system. Any kind of discontinuity in the AEI track circuit can lead to failure to sense the presence of train on the track. Following is the recommendation to reduce the effect of shunting:

- AEI track circuit condition to be monitored from the remote inspection desk for its availability and regular maintenance should be performed for it. Also, in case of detection of AEI circuit failure, a technician is to be sent out in the field for assessment and repair of the issue.

Camera failure due to electric overloading

Electric overloading of the camera is one of the high-risk causes that can hamper the safe operation of TIPS. The following are recommendations to reduce the electric overloading of cameras:

- Check for the overall power requirement by the camera system in TIPS and supply enough amperage through the breaker (CCTV 101: Camera Power Explained - Clinton Electronics, 2023). Use the 80% rule, which states that the breaker can be continuously loaded up to 80% of its continuous rating (What Is the 80 Rule in Electrical? 2023).

- Avoid extension cords and temporary connections, as this increases the risk of overcurrent because loose, tangled cords are more likely to be cut, frayed, or suffer other damage (Salvaraji et al., 2022).
- Perform regular preventative maintenance of camera systems, circuit breakers, cables, and connection points to reduce the risk of overloading, as such maintenance helps reduce system downtime (Handt et al., 2008).

Damage to the power supply cable and fiber cables

Insulation damage on the power supply cable and fiber cable can cause high-risk failure because TIPS will not capture images due to continuity loss. The power cables and fiber cables used for TIPS are mostly connected through underground conduits, and thus damage cannot be easily observed. The following are recommendations to reduce problems related to power supply cable and fiber cable damage:

- Achieve high system reliability by providing redundant power cables for the system, as these are useful when in-service power cables experience failures (Strategies for Increasing System Availability, 2001).
- Use of metal tape, fiber glass insulation, and chemical infused jacket can protect the fiber cables from damage such as animal attack, weather changes, and chemical attacks from the surrounding conditions (Fiber Optic Cables Cuts: Most Common Causes & How To Combat Them, 2023).
- Conduct regular inspection, testing, and maintenance of cable insulation to detect damage due to chemical exposure, moisture exposure, and improper installation.

Power failure due to lightening strike on TIPS

The TIPS equipment is installed with the lightning strike protection equipment. However, during one instance, the lightning strike damaged some of the TIPS equipment. Following are the recommendations for protecting the TIPS against lightning strikes (Isaed & Znaid, 2018; Okyere & Eduful, 2007):

- Thoroughly inspect the connection between air terminals and down conductors to ensure their proper functioning.

- Establish a connection for equipotential bonding with nearby metallic components, and this should be done with utmost care.
- Regular maintenance and inspection of earth pit, air terminals, and connections used for grounding and bonding of equipment.

Environmental conditions, dirt, and waterlogging

In North America, TIPS is susceptible to harsh weather conditions such as snow, wind, dirt, and rain. During the winter, snow accumulates in the vicinity of the system. When the temperature increases in the spring, snow melts and can cause water to collect around the railway tracks and CSCView camera system. Wind can cause dirt to accumulate on the equipment; such dirt will turn into mud if it comes in contact with water. These environmental conditions affect the CSCView camera system installed on railway ties for undercarriage image capture. The following are recommendations to reduce problems associated with environmental conditions:

- Install a proper drainage system to reduce waterlogging around the system, especially the CSCView camera system, which can be achieved using ditches around the rail tracks, drainpipes, carrier drains, attenuation ponds, and culverts (Railroad Track Facts… Construction, Safety and More., 2022; Engineering Track Maintenance Field Handbook, 2022; Drainage Maintenance, 2017).
- Ensure the railway tracks are built and maintained a few inches above ground level at the TIPS location, as this elevated design avoids waterlogging conditions in snowmelt and rainfall seasons. Conduct inspection and maintenance of the TIPS site before the spring and winter seasons to assess the conditions and implement actions to rectify any causes of waterlogging (Engineering Track Maintenance Field Handbook, 2022).

Failure of the power distribution system

Power distribution units (PDUs) are designed to supply power devices such as servers, networking hardware, and telecom equipment in a rack structure (Choosing A Power Distribution Unit, 2021). The study identified the failure of PDUs as one of the high-risk causes, as it can result in the failure of multiple devices involved in TIPS. The following are recommendations to reduce problems associated with failure of the power distribution system:

- Determine the type of power, type of outlets, type of circuit breakers, and possible future power consumption due to expansion work, as consideration of all of these factors can mitigate failure causes at the early stages (Choosing A Power Distribution Unit, 2021).
- Use an overcurrent protection device (e.g., fuse, thermal magnetic circuit breaker, or hydraulic magnetic circuit breaker) to prevent overcurrent conditions that can be caused by conditions such as temperature change and high current demand (Vertiv, 2016).
- Inspect and maintain the connection of power cables and outlet locking mechanisms for any loose connections that can cause a sudden drop in the system's power.
- Conduct preventive maintenance of overcurrent protection devices on an opportunity basis, as downtime for replacing such devices can be high (Vertiv, 2016).

Failure of thermostat

The thermostat signals the heater/blower system to blow snow from the CSCView camera system. The camera photos from the CSCView system, which record the undercarriage part of railcars, may be affected if the heater/blower system fails to start. The following are recommendations to reduce the failure of the thermostat:

- Calibrate the thermostat at least once per year, perform regular inspections for loose connections, and clean thermostat components, as wiring connections must be free from corrosion (Kight, 2013; What You Need To Know About AC Thermostat Calibration, 2021).

Conclusion

TIPS is a new technology for the remote inspection of railcars in the North American railway region. TIPS can perform all-around view capturing faster than manual inspections conducted in the yard by human inspectors. Continual and reliable operation of TIPS is crucial as it affects the quality of inspection of railcars. This study performed a risk assessment of TIPS using fuzzy-FMEA, a machine-learning technique for handling the vagueness of our daily language. Fuzzy-FMEA is a valuable tool for decision-making as it helps identify potential failure modes that may impact the ability of TIPS to effectively support remote inspections. This fuzzy-FMEA study used expert judgment to decide severity, occurrence, and detection ranking along with membership functions, fuzzification, if-then rules, and defuzzification methods for deriving the fuzzy-RPN. The fuzzy-RPN values indicated important high-risk failure causes such as full/partial power failure, software issues, damaged power cables, AEI tag circuit failure, environmental conditions/dirt/waterlogging, failure of air conditioning unit, and black/no images from cameras. These causes could affect the operation and reliability of TIPS. Recommendations were made to address the high-risk failure causes identified. On-field implementation of recommendations for high-risk failure causes can help organizations maintain highly reliable TIPS operation and, in so doing, sustain the high quality of railcar inspection with increased efficiency and lower costs.

Chapter 4: Assessment of Human Factors in Portal Office Inspection (POI) Technology Using the Human Factors Analysis and Classification System (HFACS) Framework

Introduction

Human factors is an area of study that focuses on optimizing human performance in the workplace to improve safety and efficiency. The consideration of human factors has gained much attention in the aviation, marine, chemical/petroleum, and railway industries (Ebrahimi et al., 2021). Despite many technological advancements in railways, significant human involvement is still required. Hence, human factors play a vital role in the complicated and safety-critical technologies of railway networks (Integrating Human Factors in European Railways Safety Management Systems, 2016). According to the European Union Agency for Railways (ERA), human factors is a branch of science that studies how people crucially interact with various system components by applying theory, principles, data, and other techniques to design and improve the performance of the human user and the system (The Importance of Human Factors in the Rail Industry, 2021):

1. Development of new tools/equipment and user interfaces to increase human performance;
2. Risk assessment and emergency planning;
3. Accident investigation for the role of human perception and human behavior; and
4. The critical condition for decision-making and teamwork.

In the past, the railway industry's tasks for technology assessment and accident/incident investigation have primarily concentrated on mechanical or technological failures (Reinach & Viale, 2006). However, there have been limited studies that study failures directly related to human factors. Human factors are important in the design phase and in routine activities as they help locate gaps in tasks and operations, which can be important for managing the safety of the system. Human factors are crucial for managing work more effectively in complex organizations, such as railways, where safety is very important for all stakeholders (The Importance of Human Factors in the Rail Industry, 2021). Therefore, the main objectives of this report are to:

- Identify the most influential human factors affecting remote CCIs performance during reviewing TIPS images; and
- Provide recommendations to improve human performance.

Literature review

Several studies have identified the role of human factors in safety performance in different industries. For instance, A Finland-based study by Poranen et al. (2021) used 15 qualitative interviews for human factor assessment of paramedics working at emergency medical services. The results show the performance of paramedics is affected by factors related to the nature of work, the organization of work-related tasks, and the work environment. Another study conducted a qualitative study to explore the experience of pilots on mixed-gender crews (Robertson, 2014). The study included 12 interviews with commercial pilots and identifies a gender impact on crew resource management. Human factors were investigated using Transport Safety Board of Canada (TSB) accident reports and results show human factors such as high workload, misuse of technology, and poor communications impact accidents in the Canadian railways (A Study of the Role of Human Factors in Railway Occurrences and Possible Mitigation Strategies, 2007).

A study in Great Britain was conducted to identify the role of human factors in the automation of railway infrastructure. The results indicate organizational influence is one of the most important human factors impacting monitoring through automation technology in railways. Introducing new technology affects how operators carry out their roles and need to adapt to the new technology. The study also reported how human factors such as situational awareness of employees, workload, human-machine interaction, supervisor instruction, and planning of tasks contribute to human errors (Dadashi et al., 2014). Another study investigates the role of human factors in the maintenance-inspection task of railway components and reports factors such as physical work environment, organizational influence, and task-related knowledge affect the performance of humans (Singh et al., 2017).

The most widely used framework for the identification of human causes in accidents/ risky circumstances is the Human Factors Analysis and Classification System (HFACS). The HFACS was initially proposed by Dr. Scott Shappell and Dr. Doug Wiegmann in 2001 for the US Navy to identify the causes of human errors and provide a framework to help plan preventive measures to reduce the occurrence of errors or incidents (Wiegmann et al., 2005). However, it has since been adopted by various sectors, such as construction, railroads, oil and gas, and marine, to identify and categorize human factors (Ergai et al., 2016). The HFACS framework is based on the Swiss cheese model, which has four levels representing the four levels of human failure (Figure 29).

Unsafe acts

The first level of HFACS is unsafe acts, which can occur for various reasons ranging from failure to follow established safety procedures to intentional acts and technology failures. Unsafe acts are classified into two categories: errors and violations (The HFACS Framework, 2014).

Error is a mistake that reflects the mental or physical activity of people who did not accomplish what they set out to do (Griggs, 2012). Based on regular operation activities, errors are divided into skill-based errors, decision-based errors, and perceptual errors. A skill-based error occurs when an operator is skilled and experienced in carrying out the task at hand but loses focus when working on other duties, leading to skill-based mistakes. These mistakes significantly impact

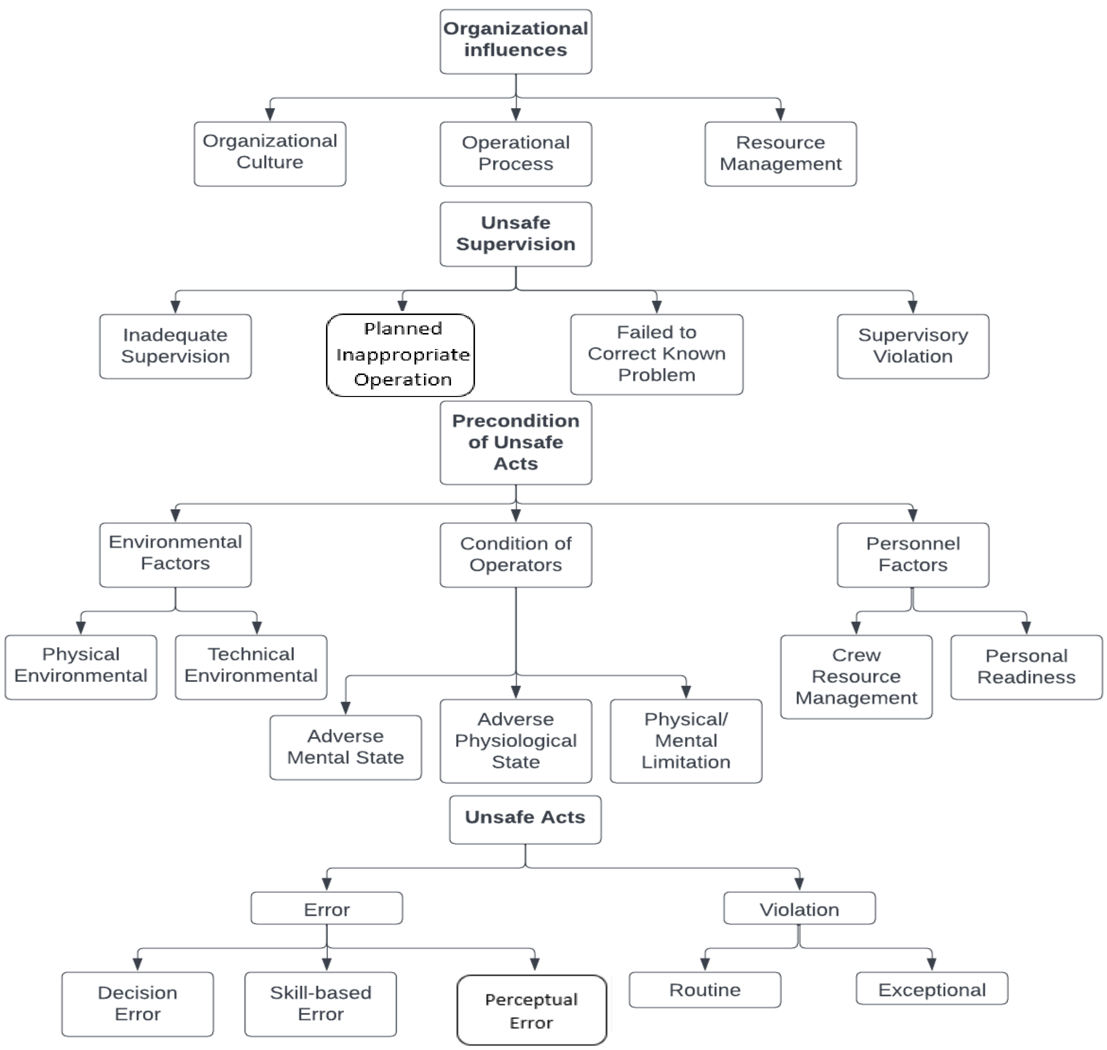


Figure 29. The HFACS framework (Mendonca et al., 2017)

regularly performed tasks such as routine maintenance checks and checklist reviews. A decision-based error occurs when an operator is aware of the protocol but performs unnecessary steps to achieve the intended outcomes in critical circumstances. These mistakes frequently result from improper procedures, poor judgment, or misinterpretation and/or exploitation of pertinent information. A perceptual error occurs when inadequate/wrong information is transmitted to the operators responsible for decision-making (Human Factors Analysis and Classification System (HFACS), 2023).

Violation means deliberate disregard for the laws and regulations. Violations are classified into two subcategories: routine violations and exceptional violations. Routine violations are habitual because of the nature of the work and are typically accepted by organizations. However, exceptional violations are not approved by the organization and are not indicative of an individual's typical behavior pattern (Human Factors Analysis and Classification System (HFACS), 2023).

Precondition of unsafe acts

The precondition of unsafe acts is the second level of HFACS, and refers to latent and/or active preconditions that impact the operator's routines and behaviors and lead to mistakes or critical circumstances. The precondition of unsafe acts is divided into three categories: environmental factors, condition of operators, and personnel factors (Celik & Cebi, 2009).

Environmental factors influence an individual's thought processes, situations, and actions resulting in human mistakes or unsafe circumstances. Environmental factors are classified into two categories: the physical and technical environment. The physical environment includes various surrounding conditions of the workplace that contribute to incidents, such as operational settings (e.g., weather, terrain, etc.) and ambient conditions (e.g., lighting, noise, vibrations, etc.). Technical environment factors include various aspects such as the design of equipment, control of processes, user interfaces, check sheets and automation strategy of the process (Yıldırım et al., 2019).

The condition of operators is divided into three categories: adverse mental state, adverse physiological state, and physical/mental limitations. Adverse mental state considers the effect of mental conditions such as diminished situational awareness, task focus, diversion, and mental tiredness brought on by insufficient sleep, which impacts performance. Griggs (2012) and Shappell & Wiegmann (2000) include physical or medical situations that make it unsafe to perform specific tasks; visual illusions, spatial disorientation, physical exhaustion, injuries, pre-existing illness, and a wide range of pharmacological and medical disorders are all known physiological states of operators that affect performance. Physical/mental limitation is when the operator does not have the physical or mental capacity to handle the demands of the operation, resulting in a critical situation. Fundamental sensory and information processing limitations are two common physical/mental limitations (Ebrahimi et al., 2021).

Personnel factors are categorized into crew resource management and personal readiness. Crew resource management examines the connections between the people and groups engaged in planning and carrying out an activity that involves human error. The personal readiness of an operator for any task is important in the organization. Personal readiness-related failures happen when an operator needs to physically or mentally prepare for duty (Shappell & Wiegmann, 2000).

Unsafe supervision

The unsafe supervision level considers how ineffective supervision can result in an unsafe circumstance. This level is divided into four categories: inadequate supervision, planned inappropriate operation, failure to correct known problems, and supervisory violation (Reinach & Viale, 2006).

Inadequate supervision means the supervisor needs to provide adequate chances to achieve operational performance through the strategic plan, chances for training, and leadership to their subordinates. Planned inappropriate operation means supervisor decisions that might be appropriate in unusual circumstances but inappropriate in routine operations, such as giving workers extended shift timings with management approval or giving employees unrelated tasks (Yıldırım et al., 2019). The situations in which a supervisor is aware of flaws in people, tools, training, or other related safety areas but permits them to remain uncorrected are referred to as failure to correct known problems. Lastly, a supervisory violation is when supervisors intentionally violate existing laws and procedures. Supervisory violations can be common and challenging to spot (Griggs, 2012).

Organizational influence

The fourth level of HFACS is organizational influences. This level considers latent conditions involving communication procedures, upper-level management actions, and policy omissions that impact the other three levels of HFACS. The organizational influences level is divided into three categories: organizational culture, organizational process, and resource management (The HFACS Framework, 2014).

A group of underlying commonly held views about a company's values, appropriate behavior for employees, and notions of what is "normal" within the organization is known as the organizational culture (Agboola et al., 2013). The term organizational process includes corporate policies and guidelines that guide daily operations inside a company, such as the development and application of standard operating procedures. Resource management considers all corporate-level decisions about the distribution and upkeep of organizational assets including staff, financial assets, technology, and buildings (Bickley & Torgler, 2021).

Methodology

The University of Alberta (U of A) and the National Research Council (NRC) conducted semi-structured interviews with remote CCIs to identify the important factors that can help to reduce errors, boost proficiency, increase safety, and ensure their comfort while reviewing TIPS images (What Is Human Factors and Ergonomics, 2022). The U of A and NRC team members had a meeting and finalized three questions for interviews. These open-ended questions allowed for the extraction of valuable and relevant information from the remote CCIs as the interviews were conducted as interactive sessions. The CPR team arranged the required facility/meeting for the NRC and U of A team to conduct interviews with four remote CCIs. These four semi-structured interviews were conducted on September 29 and 30, 2022, to investigate the routine of portal office inspection (POI) activities. Three interviews were conducted in person, and one was conducted remotely. The interviews all began with a summary of HFACS elements and an understanding of the routine shift activities associated with the participants. The three open-ended questions used in the interviews were as follows:

1. What makes a good portal office inspection? Why?

2. What are the challenges for portal office inspection? Why?

3. How can poor inspections be improved?

Data analysis

Thematic analysis was used for the qualitative analysis of interview transcripts using NVivo software v.12. Thematic analysis uses codes and themes to perform a qualitative analysis aimed at comprehending experiences and thoughts or identifying patterns from collected data (Roberts et al., 2019). Codes are defined as the most basic segments, or elements, of the raw data or information that can be assessed in a meaningful way regarding the phenomenon (Boyatzis & E, 1997). Themes are developed by clustering the codes and research text assigned to codes that combined provide a pattern or central idea in the research data.

Generally, three approaches are used for thematic analysis: deductive, inductive, and hybrid. In the deductive approach, there is some foreknowledge of the themes, and the thematic analysis results in these prepared themes (Kiger & Varpio, 2020). In the inductive method, themes are derived as the content of the qualitative research is being read and are developed according to research data. However, they may not represent the inquiries made by participants nor necessarily indicate the researcher's interests or viewpoints on the matter (Kiger & Varpio, 2020). On the other hand, the hybrid approach uses a combination of both inductive and deductive approaches. This approach helps to allow themes to arise directly from the data using an inductive approach and integrate existing research frameworks into the deductive thematic analysis approach (Fereday & Muir-Cochrane, 2006). Combining these approaches facilitates the construction of patterns from unknown elements that might not follow the deductive approach codes, leading to a more thorough study and identification of codes (Roberts et al., 2019). Therefore, a hybrid approach was used for data analysis in this research. The qualitative analysis using a hybrid or mixed approach involves six steps as shown in Figure 30:

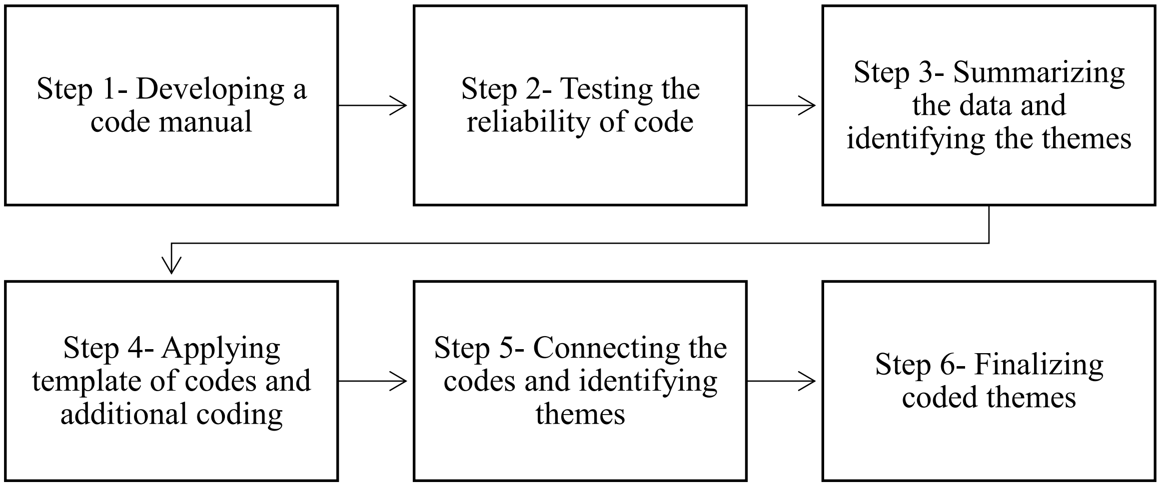


Figure 29. Steps in the thematic analysis (Fereday & Muir-Cochrane, 2006)

Step 1: Developing a code manual

The first step is developing a code manual that serves as a data management tool for organizing segments of similar or related text to assist in the interpretation of research data. For this study, a code manual was developed based on the four HFACS category elements (Table 17) (Fereday & Muir-Cochrane, 2006).

Table 17. List of initial codes for code manual

No.	Code
1	Resource management
2	Organizational culture
3	Organizational process
4	Inadequate supervision
5	Planned inappropriate operation

6	Failed to correct a known problem
7	Supervisory violation
8	Physical environment
9	Technological environment
10	Physical/mental limitation
11	Adverse mental states
12	Adverse physiological state
13	Crew resource management
14	Personal readiness
15	Decision error
16	Skill-based error
17	Perceptual error
18	Routine violation
19	Exceptional violation

Step 2: Testing the reliability of the code

This step checks the importance of codes developed in the previous step by assessing the relevance of codes to the research dataset or interview transcript. This is a crucial step as it confirms the applicability of the HFACS framework to the data collected in the interviews (Fereday & Muir-Cochrane, 2006). For instance, a remote CCI response of "This is the new tech for everyone in the job. So, he feels like there is a lot of cancel culture, he feels like change is key, and they need to educate the staff" was assigned to the code "Organizational culture."

Step 3: Summarizing data and identifying themes

This step is primarily to get familiar with the data by reading through transcripts, recognizing any patterns or themes, and observing the meanings of sentences that are available in the data. Depending on the project, the dataset may contain interviews, group discussions, recorded observations, field notes, diary entries, or other media such as photos or videos (Kiger & Varpio, 2020). This research identified codes and themes in interview transcripts according to the HFACS framework (Table 17).

Step 4: Applying the template of codes and additional coding

This step has two parts: the first is a guided approach that attaches sections of interview data to the relevant code of the coding manual, while the second is a non-confined approach that identifies the codes, based on an inductive approach, as the researcher goes through the interview transcript (Fereday & Muir-Cochrane, 2006). Interview transcripts were loaded into NVivo software, and codes were entered as nodes from the coding manual. As the reading continued, the text from each interview transcript was assigned to respective codes. As a part of the inductive approach, two additional codes (experience with technology and dedication to safety) were found while reading the interview transcripts.

Step 5: Connecting the codes and identifying the themes

Connecting codes is the process of identifying themes and patterns in the data. The codes are grouped based on their similarity as themes (Fereday & Muir-Cochrane, 2006). The research started with the codes mentioned in Table 17, to which two further codes were added, as mentioned in Step 4. Some codes were excluded from the analysis because no relevant text arose in the interview transcripts; these included organizational process, planned inappropriate operation, perceptual error, and personal readiness. The remaining codes were gathered into the different levels of HFACS, and the two additional codes (experience with technology and dedication to safety) were also treated as themes at this step. Hence, a total of six themes were identified from the analysis of qualitative data.

Step 6: Finalize coded themes

This step checks the process to allow further clustering of themes found in the coded text, if possible. This step ensures the identified themes are indicative of the initial data analysis and given codes; the earlier steps were carefully examined at this stage. The two themes added later in the analysis, namely experience with technology and dedication to safety, were combined into one theme, "Experience and safety," as they both refer to the personal element of employees. Thus, a total of five themes were finalized based on the coded text: four based on the HFACS framework plus the additional theme of "Experience and safety". The final themes are shown in Table 18.

Table 18. Finalized themes

No.	Themes
1	Precondition of unsafe act
2	Organization influences
3	Experience and safety
4	Unsafe act
5	Unsafe supervision

Results and Discussion

Thematic analysis was applied to the qualitative data collected in the semi-structured interviews. Among the four interview participants, two of the participants are part of POI technology team since its inception and the third participant has been working for more than 2 years. However, the fourth participant joined the team only a few weeks ago. Using the HFACS framework, the human factors affecting performance with POI were identified. The results of the qualitative analysis are shown in Table 19. The themes are based on HFACS, and counts show the frequency of each element in the interview transcripts.

Table 19. Themes and codes with associated counts from NVivo software

No.	Themes	Counts	Percentage
1	**Precondition of unsafe act**	**17**	**56.67**
1.1	Technological environment	8	26.67
1.2	Physical/mental limitation	7	23.33
1.3	Physical environment	2	6.67
2	**Organization influences**	**5**	**16.67**
2.1	Resource management	3	10.00
2.2	Organizational culture	2	6.67
3	**Experience and safety**	**4**	**13.33**
3.1	Dedication to safety	2	6.67
3.2	Experience with technology	2	6.67
4	**Unsafe act**	**3**	**10.00**
4.1	Decision error	1	3.33
4.2	Skill-based error	1	3.33
4.3	Exceptional violation	1	3.33
5	**Unsafe supervision**	**1**	**3.33**
5.1	Inadequate supervision	1	3.33

The results reported in Table 19 show the highest counts (17) are associated with “Precondition of unsafe act,” followed by “Organization influences” (5). However, the least counts were identified for “Unsafe supervision” (1). From the results of Table 19, it can be found that the top three codes are “Technical environment”, “Physical/mental limitation” and “Resource management”, which need to be addressed first to improve human errors in POI.

Precondition of unsafe act

Technical environment

Participants stated that various technological issues related to TIPS, such as inspecting the trains using black and white images, affect performance. They highlighted that using color images can be beneficial in terms of better distinguishing foreign objects. Additionally, TIPS provides 2D images which do not allow inspectors to measure depth or distance within an image. As an example, for a brake beam that looks bent, the amount of bent has to exceed a safety limit (set by regulators) but the remote CCIs cannot verify from the image if that is exceeded. Under such circumstances, the remote CCIs flag the issue and ask the field CCIs to verify and take action. The following are some excerpts from the interviews:

> When foreign objects are found hanging, they are very difficult to find using black & white (B&W) images. So, sometimes having a colored image can give confirmation about foreign objects.

> There is a measurement problem. They have to call Carman to verify the measurement. Field staff has the advantage of measurement.

The results of the study are in line with those of other research studies. For instance, A study by Hadj-Mabrouk (2018) in Europe for railways and another study by Nkosi et al. (2020) in South Africa for mechanical maintenance industries report that equipment used for a task, work complexity, inadequately designed equipment, improperly matched tools for the task at hand, and human-machine-interface affect performance and human error risk. Technical environment errors are mainly due to the inadequate design of the operating system, checklist, and level of automation (Scarborough et al., 2005). Re-engineering the system design and re-designing the human interface are possible solutions to improve the technical environment and reduce errors. However, based on the experience of inspectors, access to color images would be helpful for them to identify foreign objects and actual defects.

Physical/mental limitation

The participants highlighted that work often challenges their mental and physical limits. The participants reported that, on some days, they inspect more than three trains with more than 5000 images per train; this drastically increases screen time, which affects their eyes. In addition, extended and long 12-hour work shifts impact their work-life balance:

> Sometimes they need to do a lot of work. They may be working on different things. One train may take around 2.5 to 3 hours to inspect and make a report. It is an issue to handle if they are getting 3 trains back-to-back. He says that this job is tough. Not everyone can do this job. In their very busy schedule, they ask for help from different departments. This can't be a one-man show. They act as a unit and infant for lots of days. They are only getting 2 trains, so it is not terrible every day.
>
> I don't think it will be much to do with productivity or accuracy, but inspectors can have a better work-life balance with 8-hour shifts.
>
> The main problem participant-1 feels is screen time; he gets around 12 hours in a shift. So, the eye gets wet or hurts.
>
> Sometimes work is boring due to constantly sitting in the chair and remaining in the office.

A European study Hadj-Mabrouk (2018) reports that operator condition, such as physical/mental fatigue, increases the risk of human error. Furthermore, a study by Nkosi et al. (2020) identifies that a decrease in attention span, repetition of tasks (regular work), exhaustion, and stress impact the performance of employees. Mental limitations can cause a reduction in employee productivity, job satisfaction, and mood, which overall affects an employee's mental health. This can be improved by giving a manageable workload in the shift time, giving clear instructions for tasks, and recognizing employee work can help in reducing human error (Mental Health in the Workplace, 2015). Breaks during shift hours, body movement, and walking around the building can be good solutions to tackle physical limitations.

Physical environment

The participants conveyed that the physical environment of the TIPS site contributes to human performance using the POI system. Blowing snow in the winter season obstructs the camera and makes it causes images with poor quality. Conditions such as dirt and muddy water impede the camera's view, which can affect the inspection of some important components.

> Another problem is in winter; train throws snow on the cameras when it snows, so it hampers the operation or blocks the view.
>
> Weather is one of the challenges. The snow in maple creek is very light, and the blowing wind obstructs the view of railcar components in images. The mud and snow affect the image capturing in the TIPS portal.

A study by De Fabio & Petrillo (2011) reports the physical environment is the highest contributing factor to human error in railway transportation systems. A study about human error and marine safety reports that environmental factors such as temperature, lighting conditions, noise, and weather affect human performance (Rothblum, 2020). During the winter, clearing the ice from the railway tracks reduces the snow thrown on the cameras. CPR has installed fencing on the north side of the gantry to restrict the entry of blowing snow. Another way to mitigate the blowing snow is the installation of a shelter around the TIPS; however, this approach has been reported as not very successful in preventing blowing snow (Railcar Inspection Portal, 2022). Although installing a shelter that covers the cameras and restricts the entry of snow/flurries to the visual line of cameras is a potential solution. Developing a training plan using previously captured poor-quality images or images captured in the winter season for remote CCIs could also help to improve human error.

Organization influences

Resource management

Participants stated that high employee turnover in the organization also affects the performance of the POI. Training more people and retaining experienced personnel is good for the organization and efficient working of shift tasks:

> Training more people would be good, having a second person is good and in the case of two trains that would help a lot. Having a backup will give them less stress. Currently, only a single person works at a desk; if they need help, they need to call someone from the Network Management Centre (NMC) department. Also, NMC is very busy in winter, so it will be hard for remote CCI to get the backup person at that time.

> I think they need to train more people from the NMC department because they have been working on a train for a long time, and it would be super easy to train them.

> CPR is going through a lot of organizational change. And people leave this job and need new talent, so it will take more time to train a new person.

Organizational resources are a contributing factor that affects human performance in railway operations (Kyriakidis et al., 2018). Poor operating efficiency, poor utilization of the workforce, and poor selection/retention of the workforce are related to human resource management in railways (T & K, 2016). Humans as a resource can be managed by considering them as part of the organization and developing their overall knowledge, skills, creative abilities, talents, aptitudes, and potential to carry out the tasks and responsibilities successfully delegated to them (Ahmad, 1997). There were some new recruits that happened around the timeline of the interview as CPR has identified the need for new team members for POI technology. Good compensation and better welfare policies are other important factors that help manage human resources (T & K, 2016).

Organizational culture

The participants also stated how organizational culture affects human performance during POI. The field CCI in the yard sees the POI as creating extra work, and some CCIs consider this technology a competitor for their job. Information may not be effectively transferred between the yard and office inspector if the yard and remote CCI do not get along:

> This is the new tech for everyone on the job. So, he feels like there is a lot of cancel culture, he feels like change is key, and they need to educate the staff.

> I feel that field workers feel competition with remote CCI, which is not right. The ultimate goal of remote CCI is to make trains safe, but Carman feels threatened by this new technology.

A study of human errors on the UK railway by Kyriakidis et al. (2018) reports organizational safety culture is the highest contributing factor to human errors. Another study highlights how the absence of a strong safety culture affects human performance (Rafieyan et al., 2022). Organizational culture can be influenced by the business environment, leadership, and management practice (Agboola et al., 2013). The organizational culture can be improved by the leader of the organization, who sets an example for every employee of the company. Also, clear communication of policies and company vision, managing trust in the workforce, offering learning opportunities, mentoring and coaching, and people safety-oriented policies can help build and manage good organizational culture (Tenney, 2022).

Experience and safety

Dedication to safety

The hybrid method revealed this code during the thematic analysis of interview transcripts. The participants reported that the safety dedication of individuals is an important human factor that affects the performance of POI. Individuals must be open to getting feedback from supervisors or colleagues and understanding safety in every aspect of POI technology-driven inspection:

> Seriousness for the project is a must for everyone on the team. They need to be dedicated to the process.
>
> The very important thing for any inspector is to get feedback from the supervisor or CCI about the inspection work he/she has conducted. Due to constant feedback and tips from the supervisor, remote safety inspectors can review his/her work and improve in identifying defects.

An India-based study by Poddar et al. (2015) performed human factor analysis for railway coach and bogie maintenance operations. This study reveals that personal dedication to safety and motivation directly impacts the reliability and safety of the railroad system. The safety dedication of a team can be developed by encouraging the group in different ways, such as recognition, incentives, getting feedback from the team, celebrating safety week, and developing a safety culture fueled by the involvement of management leaders of the organization (Best Ways to Motivate Employees to Become More Safety Conscious, 2022).

Experience with technology

This code was also derived from the thematic analysis of interview transcripts. The participants conveyed that an individual's experience with the technology is a human factor that affects POI performance. Experienced inspectors indicated they could handle situations such as multiple train inspections and prioritizing tasks better than newly hired ones. Also, their experience with TIPS allows them to conduct overall inspections in less time than new hires and to better manage critical situations:

> Due to my current experience, I am not feeling any rush while working. It is always important

> to prioritize the train.
>
> Time to inspect the train is higher because he is new; as a more experienced guy, he has built a memory muscle and can quickly inspect the car.

An Iran-based study of oil and gas industry found that lack of experience in a given task contributes to human error (Jafarinodoushan & Abdar, 2021). A UK railway-based study reports that familiarization with task/operation is the second-most important factor affecting the chance of human error (Kyriakidis et al., 2015). Providing on-the-job training and conversing with senior employees are possible ways to increase employee experience with technology. Conducting weekly/bi-weekly meetings with the team and brainstorming sessions are other ways to address existing issues.

Unsafe act

Decision error

The participants reported that poor decisions and incorrect responses to specific defect identification sometimes affect human performance with POI technology. For instance, when a remote CCI is unsure about whether the defect in the image is valid or just a foreign object, the/she marks it as defective car:

> Also, sometimes they can make decision errors like they come up with something that they think is a defect, but it is not. For example, grease on the wheels often looks like a crack, but it is not. If they bad order that, Carman must walk around that wheel and ensure there is no crack.

This practice is good because remote CCIs don’t want to miss any defects that cause accidents of train. A UK-based analysis of railway accidents using the HFACS framework reports that decision errors are the second-most contributing factor to the unsafe act category that causes human error (Madigan & Golightly, 2016). Poor decision-making and judgment were reported in decision errors in a study from China (Zhan et al., 2017). Decision errors are often due to improper procedures, incorrect decisions, or merely a misinterpretation or misuse of available information (Module 4 - Human Error, 2010). Offering improved and correct information, automation, and, to some extent, training can reduce decision errors in any operation (S. Shappell & Wiegmann, 2009). More formal instruction or procedural tools such as checklists might be beneficial in terms of reducing the frequency of decision errors by human operators (Patterson & Shappell, 2010).

Skill-based error

The participants stated that they sometimes found an important update for the team and other departments, but forgot to communicate it due to failure of memory or attention:

> Many times we have to store something in their mind to communicate later with other departments; it becomes stressful when that happens.

An investigation of 407 railway accidents/incidents in China revealed that skill-based errors are one of the top four causes of human error in the HFACS framework and can lead to accidents/incidents (Zhou & Lei, 2018). A study by Baysari et al. (2009) used data from the Australian transport safety bureau (ATSB) and HFACS framework for human error classification. This study found that skill-based errors significantly contribute to the unsafe act category. Skill-based errors can be due to high workloads, distractions, work deadlines, fatigue, and other demanding factors of the workplace (Morgan et al., 2016). One potential way to reduce skill-based error is the use of the STAR methodology, which is very effective for new technology with a high degree of automation (Reducing Errors and Improving Safety Through a Human-Performance Initiative, 2023). Furthermore, refresher training, improved procedures, and practice protocols can help reduce skill-based errors (Reinach & Viale, 2006).

Exceptional violation

According to participants, ignorance of any issue or task is one of the major human factors that affects the performance of POI:

> I would say ignorance is the enemy while working on POI; small details can play a big role.

A US-based study about restricted railway speed train accidents reports that violation of rules is one of the major contributors to railway accidents (Zhang & Liu, 2020). The violations are avoidable types of human errors that can be contained by providing more training about the task's risk and the consequences. Planning, supervision, analyzing the potential for rule violations, analyzing and learning from violations, and designing better procedures, including meta-rules to deal with exceptions, are the preferred methods to reduce violations (Hale et al., 2003). Encouraging employees to report the violation and to be more vigilant about the procedure can reduce exceptional violations. Senior management can change the task procedures, reducing employee violations and the risk associated with the task (Hudson & van der Graaf, 1998).

Unsafe supervision

Inadequate supervision

The participants reported that supervision is key for the performance of remote CCIs using TIPS images. Only one inspector works in the office during night shifts, and no supervisor is available. The participants reported that when they had questions about the bad order of railcars, they had to call their supervisor at night:

> I think that sometimes reaching to director or manager is hard. While working in night shift with no supervisor, and if there is a bunch of bad order that they are unsure about, they need to call the supervisor at midnight, around 2 am- 3 am night, when they are sleeping, inspector feel bad to call and many times don't call.

A study by Kumar & Sinha (2008) in India about human error in railways states that poor supervisory actions and decisions made in the railway industry lead to extremely risky and accident-prone circumstances. Failing to provide guidance, review daily performance, and notice mistakes in tasks are aspects of inadequate supervision (Shappell & Wiegmann, 2000). Regular supervisor training is necessary to give the team the appropriate input to improve the supervision of inspection tasks. Weekly or bi-weekly review assessments of remote CCI work can provide input about their inspection techniques in the early stages of their career (Zhan et al., 2017).

Synthesis of remote CCI responses to interview questions

What makes a good portal office inspection and why?

- All of the interviewees unanimously agreed that TIPS is ground-breaking technology. TIPS can capture images of moving railcars without interrupting the operation. Using this technology, remote inspectors can inspect the train from all possible angles from the comfort of their offices. The railcar images are black and white with zoom-in, zoom-out, contrast adjustment, and very high resolution, which facilitates easy inspection of tiny details of the railcar.

- The alternative to TIPS is a comprehensive inspection of railcars by field inspectors. Manual inspection of railcars requires nearly 4-5 people for inspection of a full train and takes nearly 2-3 hours, depending upon the number of repairs. This manual inspection activity can be challenging during harsh winter conditions. In addition, the components located under railcars are less visible and difficult to each. Using TIPS, a remote CCI can inspect various components of railcars using images at their desk while the train is still moving and thus improve productivity. This would also allow the inspectors in the field to focus more on repairing than finding defects.

- A communication protocol between the inspection desk and the yard is important. Whenever a remote CCI finds any severe defect that can cause derailment or failure of train operation, they immediately inform the RTC and yard. Remedial actions are then taken to eliminate the cause at the yard or on the railway tracks by stopping the train. Thus, this technology helps to identify potential causes of accidents before they occur.

- Railcar images can be easily tracked on the TIPS server. office inspectors can review the previously captured images of the railcar and understand the defect propagation over a few passes of the portal. The images can be useful in training new employees for POI.

What are the challenges for portal office inspection, and why?

- All of the interviewees identified that on-site weather factors such as blowing snow and muddy water affect the operation of the TIPS. During the winter, blowing snow obstructs some portions of railcar images. Recently, they also encountered the bottom camera (CSCView) getting clogged due to improper drainage of the bottom tie, which resulted in the obstruction of one camera. This kind of weather or environmental factors partially or completely affect the operation of the TIPS.

- The TIPS is comprised of many electronic devices, which can affect the reliability of the overall system. Some issues with cameras and connecting cables have already created reliability problems for the TIPS. The camera is positioned on the portal to cover all important areas, but some locations remain inaccessible, such as the top of the brake shoe.

- The usual shift duration for an office inspector is 12 hours. During regular days when train flow is high, a person must spend most of the time looking at a screen. High screen exposure can result in strain on the eyes and body. The number of images captured per railcar is also high. However, these images cover almost all angles (front and back) and thus can help to identify defects in railcars. Inspecting a train using TIPS takes 2-3 hours of highly repetitive work. The repetitive nature of the work and the potential loss of concentration increase the chances of decision errors.

- Images are black and white, which helps eliminate shadows of objects. However, this can pose problems when an inspector needs to confirm any grease marks, oil spills, or foreign objects. Hence, access to colored images can be helpful in some scenarios.

How can poor inspections be improved?

- The POI can be improved by training inspectors and providing feedback on their inspections. Supervisors/managers can play a vital role in this respect. Constructive feedback for employees is valuable input on their work, and passing on experience to the team can impact the effectiveness of the team and POI approach.

- Field inspector awareness about POI is very important because feedback from the field to the office desk is crucial for educating employees about any defects they missed.

- Training more employees on POI would enable shifts to be reduced from 12 hours to 8 hours, which would help to improve the effectiveness and productivity of the office inspections. With reduced shift hours, desk inspectors can maintain a work-life balance and have less screen time. To overcome this challenge, CPR has recently recruited new team members for POI team.

- Reducing the number of images per railcar is one possible way to reduce screentime exposure.

- The availability of color images could potentially help desk inspectors to better discern grease marks, oil spills, and foreign objects.

- The inspection of railcars from the top is not providing enough zoomed in images and thus not useful in capturing any defects for the top of coupler and top of railcars. Coupler inspection from the top side is also not feasible using the available setup. Both of these aspects could be improved.

- The images captured for the trains are stored for a limited time and then overwritten by new images. However, the deleted images have value with respect to training employees. Hence, more storage space would be beneficial.

Conclusion

This collaboration between NRC, CPR, and the U of A on human factors assessment provided useful inputs and helped smooth the conduct of the semi-structured interviews. The human is one of the important entities in POI, and factors affecting human performance are critical for enhancing the overall performance of this technology. Semi-structured interviews and thematic analysis were employed to analyze latent and underlying causes of human error when using POI technology. The interviews were conducted with remote CCIs with a wide range of experience and helped capture important qualitative data for human factors assessment. The findings of the thematic analysis indicate precondition of unsafe acts is the most contributing theme, followed by unsafe supervision. Among the top two themes, the technological environment, physical/mental limitation, and failure to correct a known problem were the most frequent codes. This indicates that human-technology interaction and supervisory inputs/actions are critical issues with respect to reducing the probability of human errors and improving the performance of POI technology.

Experience and safety was an additional theme that emerged from the interview data, and considers how the level of experience and safety dedication affect the chances of human error with POI technology. Chances of human error decrease with increasing level of experience with POI technology. The least contributing theme is unsafe supervision and the lowest percentage for unsafe supervision indicates the CPR's effort to reduce human errors and shows good supervision practice for POI. The findings of the human factor analysis and recommendations suggested by this research can help CPR minimize the frequency of human errors, improve human performance, and improve the safety of their railway fleet on the railway network.

Chapter 5: Artificial Defect Simulation on Railcar Components for Automated Machine Vision Inspection System (AMVIS)

Introduction

The original plan was to check the repeatability of defects by passing it multiple times through TIPS camera system, but it was not covered here due to operational challenges of railway operation. So, this research is focused on assessing the visibility of safety-critical defects in the images taken by CPR's Maple Creek TIPS. The list of safety-critical defects were determined by the project's steering committee and includes: a broken wheel, cracked axle, missing axle cap screw, truck bolster crack, missing/bent truck spring, bent brake beam, bent / cracked side sill, cracked center sill, cracked coupler knuckle, cracked centre sill, cracked coupler body, hand brake, and angle cock. The preliminary analysis suggested that some of these defects have a very low frequency of occurrence and it's possible that they may not be found on images during the course of this project.

Furthermore, the current state of using TIPS requires human inspectors to review images. Such inspections are tedious and time-consuming and as discussed in the report of "Assessment of Human Factors in Portal Office Inspection (POI) Technology Using the Human Factors Assessment and Classification System (HFACS) Framework", are subjected to human factors effect. Using effective AI algorithms can potentially offer more accuracy and consistency than visual inspection and the capacity to gather and organize massive amounts of visual data quantitatively (Sawadisavi et al., 2009). The algorithms are trained on sample datasets and their effectiveness are correlated with the number of samples or cases they have been trained on. However, as mentioned previously, some defects do not occur very frequently and thus prevent the development of highly efficient AI algorithms.

To overcome the abovementioned limitations, the simulation of low-frequency defects was conducted in this project to test their visibility from TIPS images and enable creating a larger dataset of them for future training of AI algorithms. The researchers of NRC provided useful guidance in proposing and simulating defects in the field environment. This project was focused on simulating the following defects on the railcar components: cracked wheel, cracked axle, and missing truck springs, etc. These fake defects can replicate the scenario of actual defects on the rail car.

Therefore, the objectives of this study are:

- To simulate rare artificial (fake) defects on the railcar components to see how defects look in the POI technology environment; and
- To check the reliability of POI technology and how the remote CCIs respond to rare defects.

Literature review

Various organizations, such as Transportation Technology Center, Inc. (TTCI) and researchers at the University of Illinois at Urbana-Champaign have conducted studies to develop fake defects on railcars. According to the TTCI research (Witte & Lindeman, 2017), there are five different ways to introduce fake defects onto railcar undercarriage components to determine defects' detectability using machine vision algorithms. The use of silicon caulk, magnets or magnet sheets, grease pens, white plastic containers, or wires are a few examples of potential methods.

For railcar undercarriage inspection, TTCI used silicon caulk for artificial defects for Vehicle Undercarriage Examiner (VUE^{TM}) from Duos technologies (Witte et al., 2017). This experiment was conducted at the accelerated service testing (FAST) facility at the TTCI center in Pueblo, Colorado. For defect detection, TTCI introduced an artificial (synthetic) defect on the center sill of the railcar. This defect was a crack that was created by silicone caulk (Figure 31).

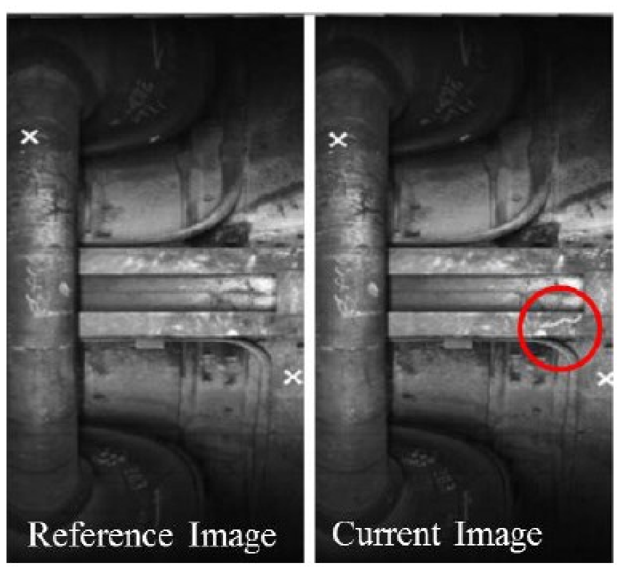
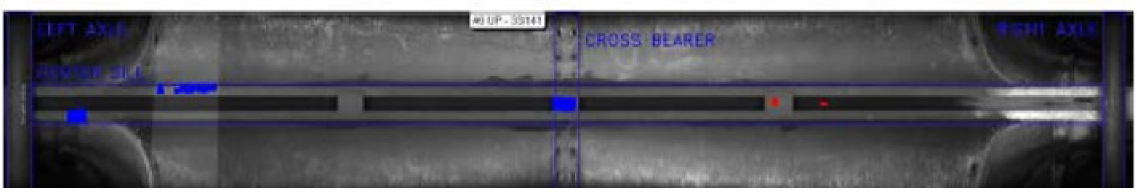


Figure 30. Silicone caulk used for fake defect (Witte et al., 2017)

In another experiment, TTCI used magnets to generate anomalies on railcars. Notably, the size of the magnets was larger than the threshold limit of the detection system to simulate the defect (Witte & Lindeman, 2017). Another inspection from TTCI mimicked the defects of the undercarriage of the railcar using magnetic sheets, a grease pen, a white plastic container, and wires. Initially, they used white and grey containers for defect generation, but the grey container was difficult to simulate the defect because of its similar color to the undercarriage of the railcar. On the other hand, the white containers simulated the defects correctly, and the algorithm identified defects. The wires were used to replicate the crack defects on components. In addition, a grease pen was used to generate the crack defect on the center sill of the railcar. The defect size must be larger than the threshold limit of error detection of the algorithm. They used a 1-foot x 1-foot white magnetic sheet for defect generation in the railcar (Witte & Chaparro, 2015). Figure 32(a) shows the defects detected by the system, and Figure 32(b) shows the objects used in simulating artificial defects.

a)



b)

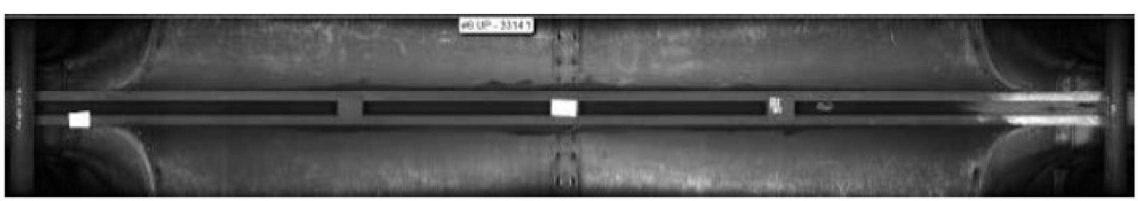
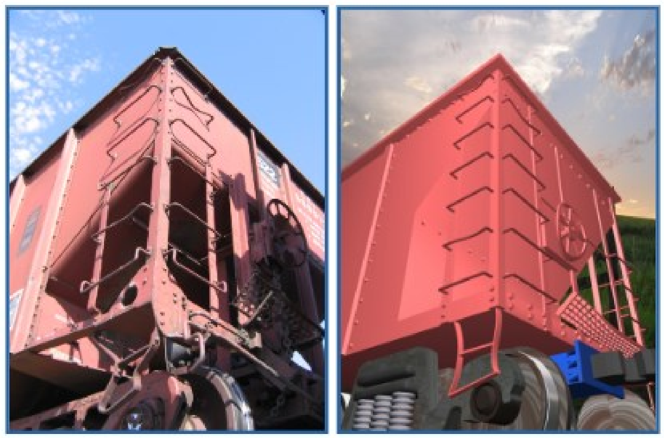


Figure 31. White container, grease pen, and magnetic sheet used for fake defect (a) detection by the system for fake defect objects and (b) fake object image.

The researchers at the University of Illinois at Urbana-Champaign used a virtual model of a railcar for defect generation. This model was used to develop defects, which were expected to be rare during algorithm development for machine vision inspection techniques. This virtual model also helped the team to test the defects under different lighting situations, on different railcar types, and from different camera angles (Edwards et al., 2007).



(a) (b)

Figure 32. A Virtual model of an open-top hopper for defect simulation (a) actual railcar, (b) virtual model of a railcar

As seen in Figure 33, the virtual model of the railcar shows the high-level 3-D model of the open-top hopper-type railcar. The deformation of the ladder can also be seen in the virtual model as it is visible in the actual hopper. The researchers have used Autodesk's 3DS MAX 8 computer modeling software for developing a 3-D model of an open-top hopper (Edwards et al., 2007).

Methodology for defects simulation

To simulate defects on the railcars, we targeted defects that were pre-identified from the AMVIS project such as the cracked wheel, broken axle, broken coupler, broken side sill, cracked brake beam, and broken truck spring. The location for the simulation of defects on railcars was selected based on discussions with the highly experienced Transport Canada regional inspector, CPR railway yard supervisor, CPR's field CCIs, and NRC researchers. The U of A team conducted the experiment at CPR Alyth yard, Calgary, and the CPR team managed the necessary arrangements for conducting this part of the research. The simulation of fake defects was conducted using metal wire, magnets, and silicon caulk. We conducted this experiment in two different parts:

1. Part 1-Defect simulation of stationary railcar;

2. Part 2-Defects simulation on railcar that passed through TIPS.

Part 1- Defect simulation of stationary railcar

The first part of the study was conducted at a CPR yard located in Alyth, Calgary, on July 22, 2022. We simulated different defects, such as a cracked wheel, cracked center sill, cracked knuckle, cracked axle, and cracked truck spring using magnets and metal wire. The images were captured using a phone camera.

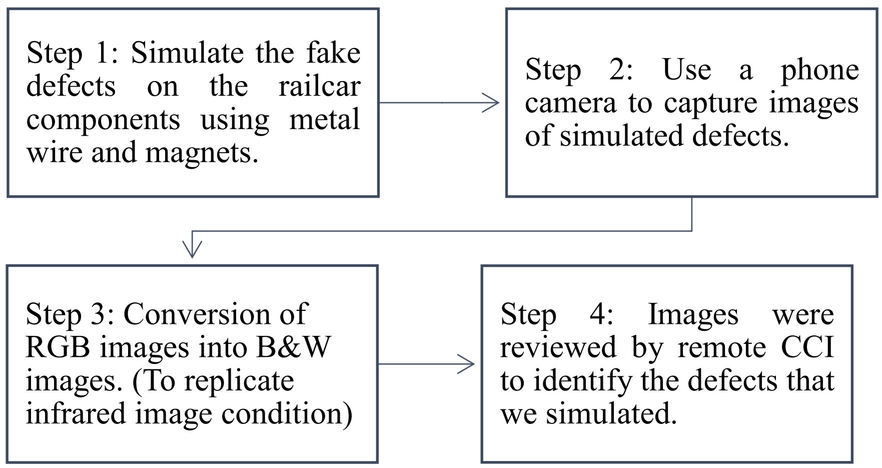


Figure 33. Fake defect simulation steps for Part 1

This part included simulating defects on components of a railcar that is in a stationary condition. Figure 34 shows the procedural steps for part 1 of the experiment. The purpose of this step was to check how we can install the defects on the components of the railcar before implementing them on moving railcars.

Part 2-Defects simulation on railcar that passed through TIPS

We conducted part 2 at the CPR yard located in Alyth, Calgary, on January 09, 2023. The purpose of part 2 was to check how simulated defects look in the POI technology environment and how remote CCIs respond to simulated defects. Thus, we simulated the defects on components of the railcar, which will pass through the TIPS portal. Figure 35 shows the procedural steps for part 2 of the experiment.

We developed different fake defects such as broken truck springs, cracked side sill, cracked knuckles, broken brake beams, broken step sill, and cracked yokes using magnets, metal wire, and silicon caulk. These defects were simulated on two different railcars, DOWX20758 and CCBX71731.

- DOWX20758 railcar was simulated with three defects, a cracked coupler, a cracked yoke, and a broken truck spring. The railcar DOWX20758 departed from Alyth yard and passed the TIPS portal on January 09, 2023.
- CCBX71731 railcar was simulated with five defects, a broken truck spring, two cracked side sills, a broken brake beam, and a cracked step sill. CCBX71731 departed from Alyth yard on January 15, 2023, and passed the TIPS portal on January 16, 2023. All five defects were visible in the images which were captured by TIPS portal camera systems.

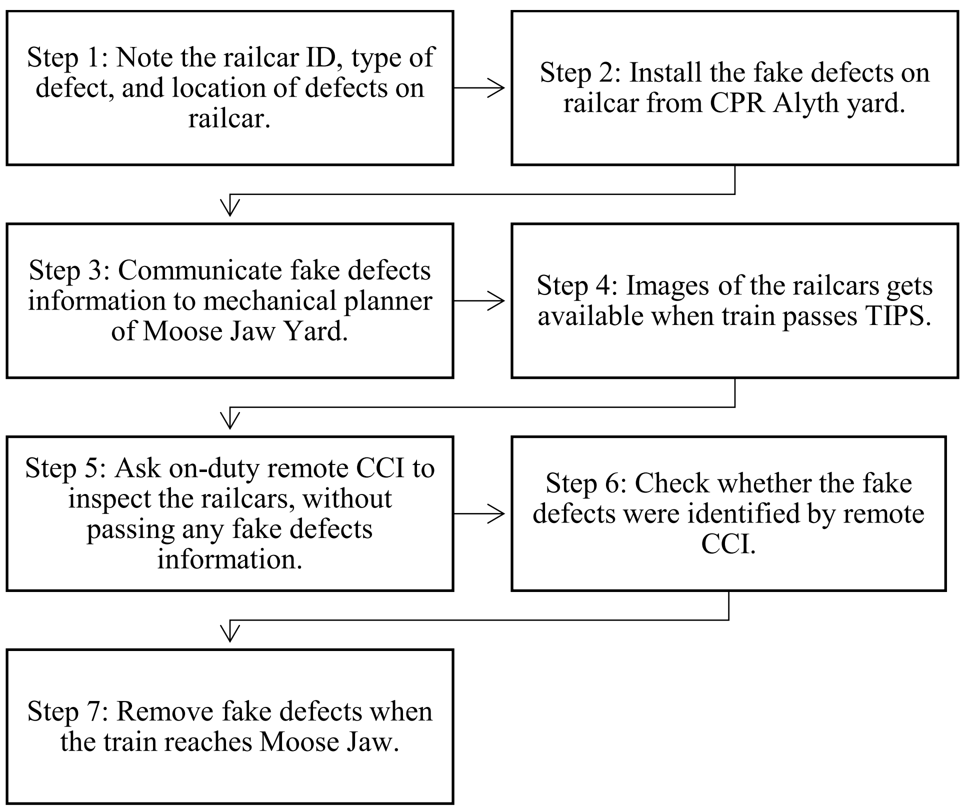


Figure 34. Fake defect simulation steps of Part 2

We removed the simulated defects in Moose Jaw yard, from the railcars once they had been passed through Maple Creek, Saskatchewan's TIPS camera system. Because the railcars may depart from the mine loading site for other railway operators, it is extremely unlikely that the same railcars will return to CPR rail lines and pass via The TIPS camera system on their subsequent journey.

Otherwise, these flaws might mislead other railroad operators. Thus, we were unable to determine the repeatability of flaws in part 2 of the experiment.

We did not simulate cracked wheel and cracked axle railcar defects in the part 2. It is not possible to simulate a wheel crack using metal wire and magnets since the railcar wheel is rotating at a fast rate and the equipment may come off from the railcar. Also, we didn't simulate the cracked axle. Because it is one of the high-risk defects and seeing cracked axle through TIPS image can cause implementation of critical procedure such as stopping of train and taking out the railcar from fleet immediately. This could lead to various consequences in railway operation and thus we didn't simulate it.

Results and Discussion

The results of the defect simulation are analyzed using captured images. For part 1, images were captured using a phone camera, and for part 2, images were captured by TIPS camera systems located in Maple Creek, SK.

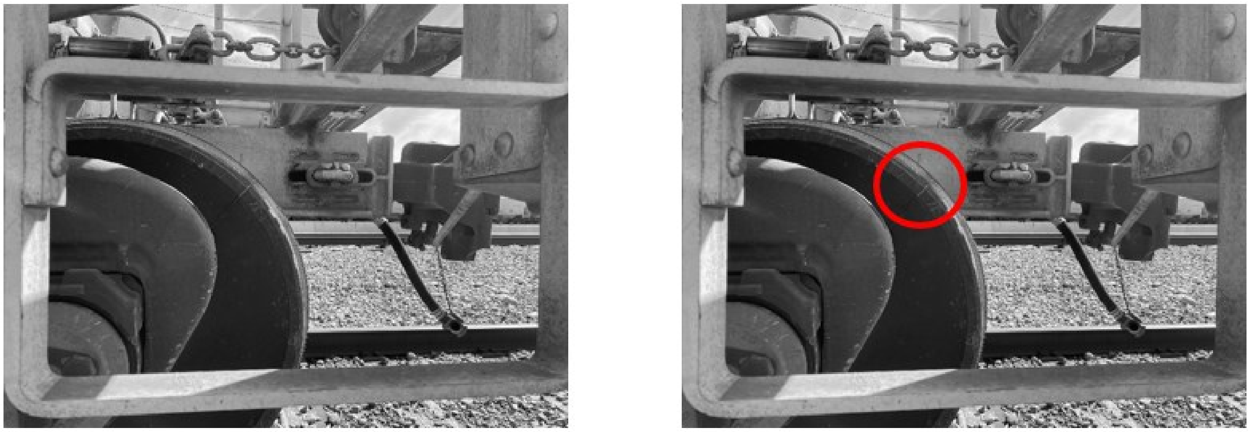
Results and discussion of part 1 (Defect simulation on stationary railcar)

The images from the TIPS camera system are IR images, but for part 1 the images were colored in type because we used a phone camera for image capturing. Thus, we converted the phone camera captured images to IR images which remote CCI usually sees on their computer system. We used Python software code to convert red-green-blue (RGB) images to (B&W)/IR images (Figure 36).

(a) (b)

Figure 35. (a) RGB image from the camera, (b) B&W image from the python code

Fake defect 1-cracked wheel



(a) **(b)**

Figure 36. (a) Wheel (b) Cracked wheel with simulated defect

A crack on the railcar wheel was simulated using metal wire, and magnets were used to keep the metal wire in its position. Figure 37(a) is a captured image, and Figure 37(b) shows the location of the simulated crack at 2'o clock position.

Fake defect 2-cracked center sill-2 location

(a) (b)

Figure 37. (a) Center sill, (b) Cracked center sill with simulated defect (Location-1)

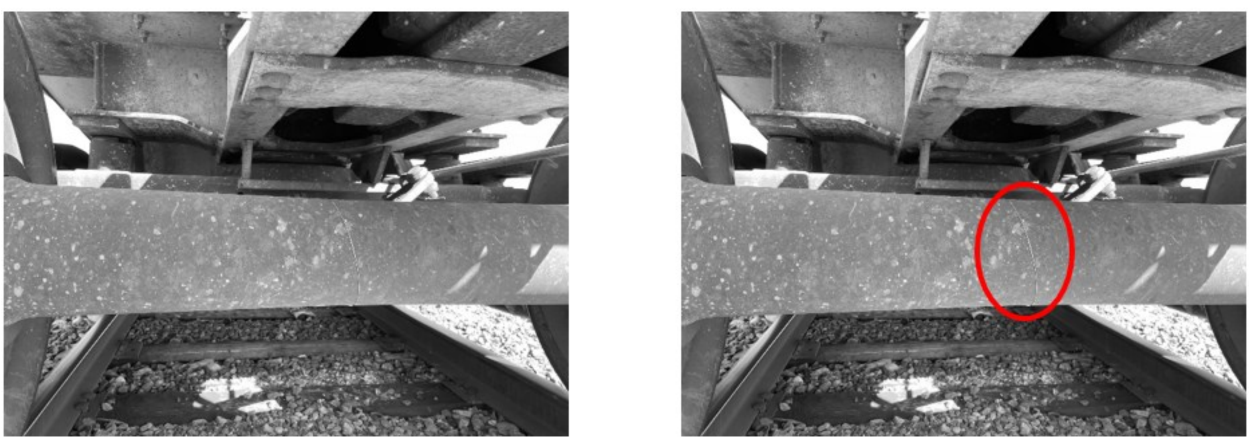
A crack on the center sill was simulated using metal wire, and magnets were used to keep the metal wire in its position. Figure 38(a) is a captured image of the center sill, and Figure 38(b) shows the location of a simulated crack on the center sill.

(a) (b)

Figure 38. (a) Center sill, (b) Cracked center sill with simulated defect (Location-2)

Another crack on the center sill was simulated by wrapping metal wire around the corner of the center sill at the second location. Figure 39(a) is captured image of the center sill, and Figure 39(b) shows the location of a simulated crack on the center sill.

Fake defect 3-cracked truck axle



(a) (b)

Figure 39. (a) Truck axle, (b) Cracked truck axle with simulated defect

A cracked truck axle defect was simulated by wrapping a metal wire around the axle. Figure 40(a) is a captured image of the truck axle, and Figure 40(b) shows the location of a simulated crack on the truck axle.

Fake defect 4-broken truck spring

(a) (b)

Figure 40. (a) Truck spring nest, (b) Broke truck spring with simulated defect

Wrapping metal wire around the spring coil simulated a broken truck spring. Figure 41(a) is captured image of the truck spring nest, and Figure 41(b) shows the location of the simulated crack on the truck spring coil.

Fake defect 5-Cracked coupler

(a) (b)

Figure 41. (a) Coupler knuckle, (b) Cracked coupler knuckle with simulated defect

A crack on the coupler knuckle was simulated using a metal wire. We kept the metal wire in its position as per Figure 42(a) and captured an image with a phone camera. Figure 42(b) shows the location of the simulated crack on the knuckle.

The on-duty remote CCI identified all the simulated defects on various railcar components using the B&W images. The results of part 1 confirmed the use of metal wire and magnets is good enough to create defects on railcars; therefore, we proceeded to the second part, which involved implanting fake defects on the moving railcar to identify defects on the TIPS camera environment.

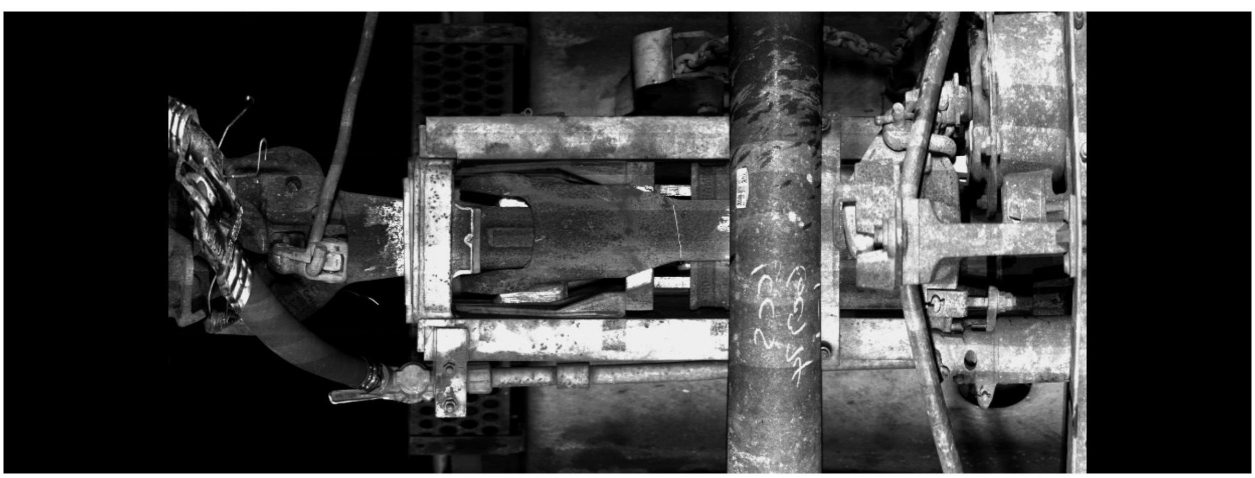
The images in part 1 were captured using a standard phone camera. Thus, some images had shadows of railcar parts. However, the TIPS technology uses IR image-capturing cameras, which nullifies the effect of shadows and sunlight.

Results and discussion of part 2 (Defect simulation on railcar that passed through TIPS)

Fake defect 6-cracked yoke

A crack on the yoke was simulated using a metal wire. We wrapped the metal wire on the yoke, and Figure 43(a) is the obtained image from the CSCView camera system of the TIPS portal. Figure 43(b) shows the location of the simulated crack on the yoke.

a)



b)

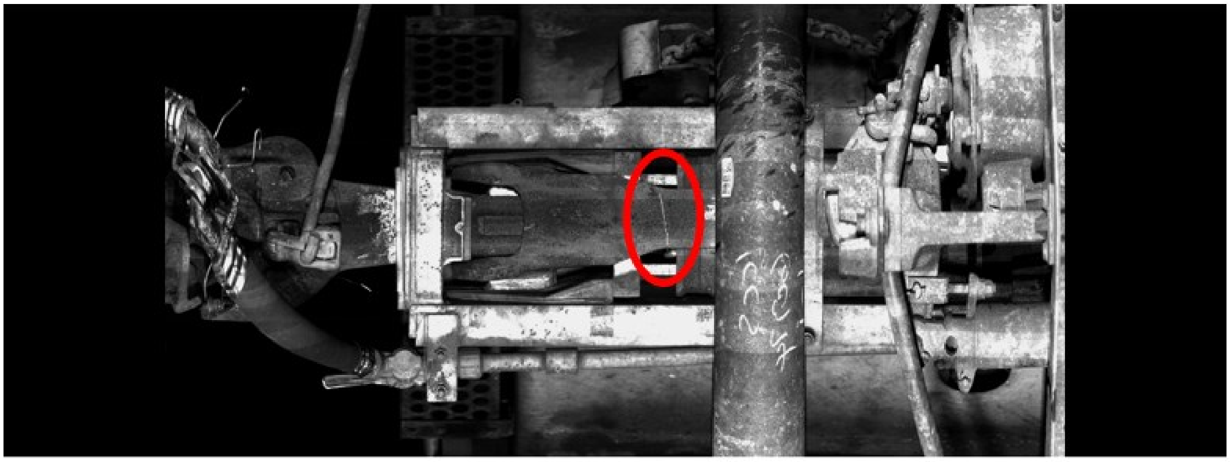
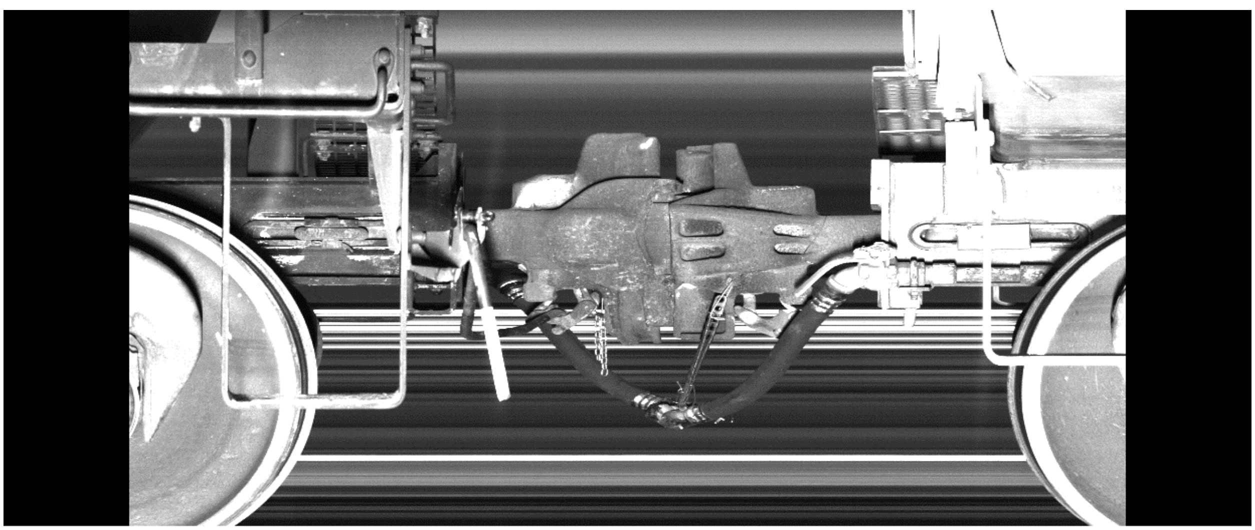


Figure 42. (a) Yoke, (b) Cracked yoke with simulated defect.

Fake defect 7-cracked coupler

A crack on the coupler was simulated using a metal wire and magnet. We kept the metal wire in position and used a magnet to hold the metal wire in position. Figure 44(a) is the obtained image from the AHView camera system of the TIPS portal. Figure 44(b) shows the location of the simulated crack on the coupler.

a)



b)

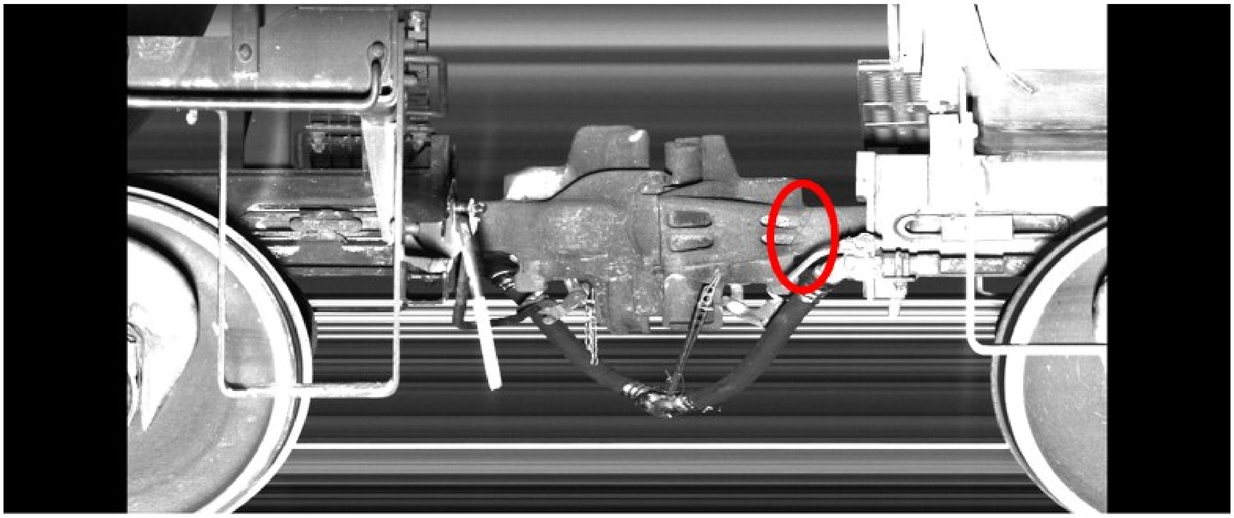
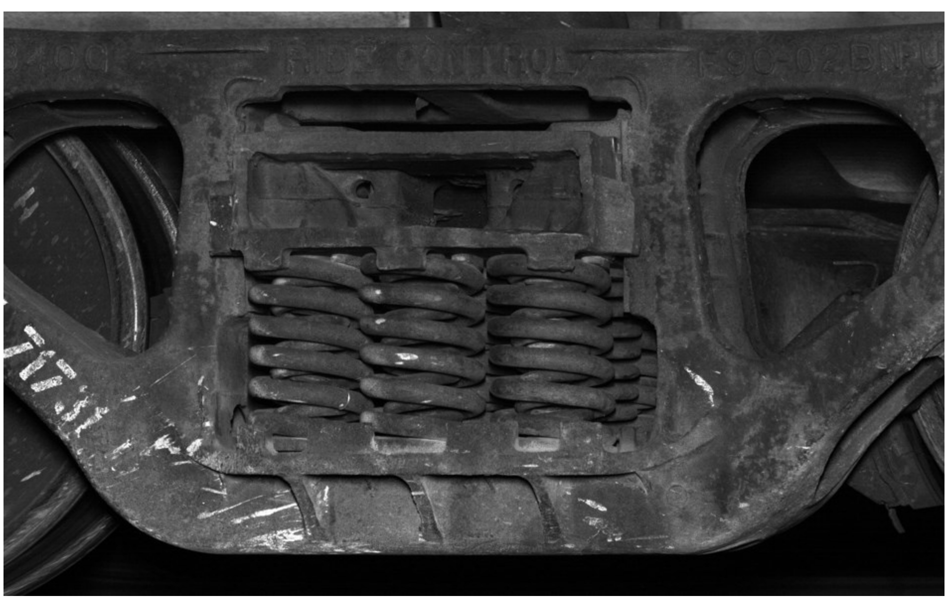


Figure 43. (a) Coupler, (b) Cracked coupler with simulated defect

Fake defect 8- broken truck spring

A crack in the spring was simulated using a metal wire. We wrapped the metal wire around the coil of spring in the spring nest. Figure 45(a) is the obtained image from the TruckView camera system of the TIPS portal. Figure 45(b) shows the location of the simulated broken truck spring.

a)



b)

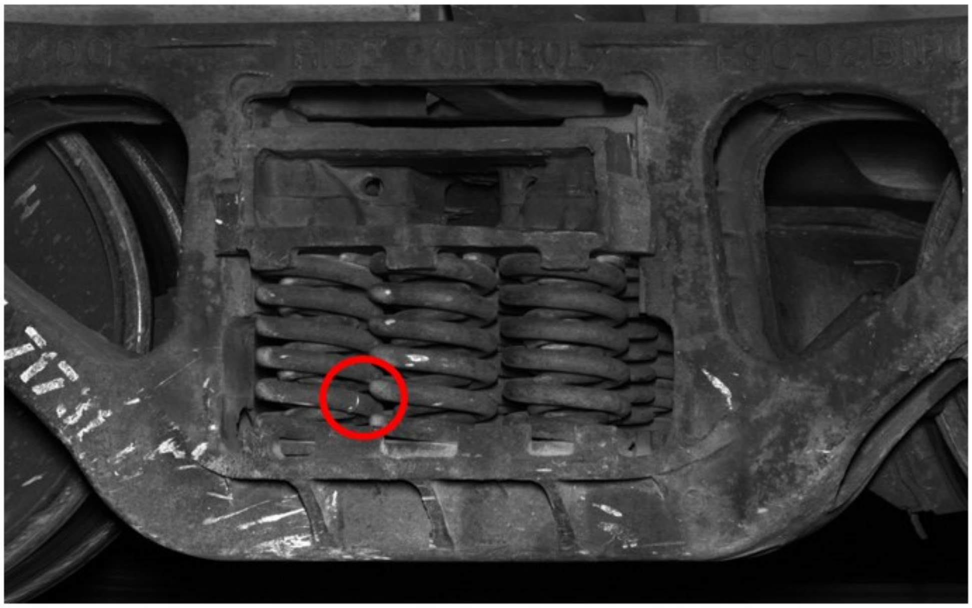


Figure 44. (a) Truck spring, (b) Broken truck spring with simulated defect

Fake defect 9 -Cracked side sill – at 2 locations

Cracks on the side sill were simulated using a metal wire, magnets, and silicon caulks. We placed the metal wire on the side sill and used magnets and silicon caulk to hold the metal wire in its position. Images in Figures 46(a) and 47(a) were obtained from the TIPS portal TrainView camera system. Images in Figures 46(b) and 47(b) show the location of the simulated side sill cracks.

a)

b)

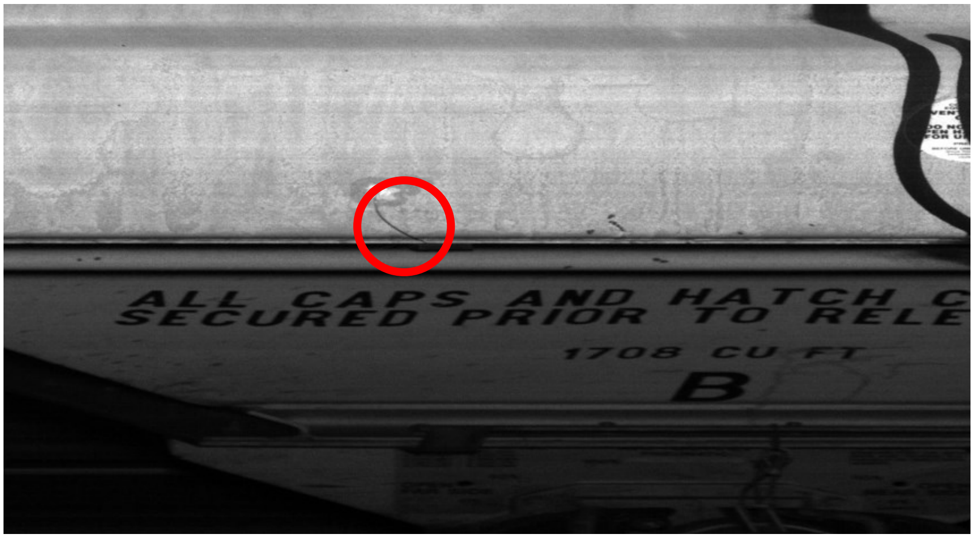
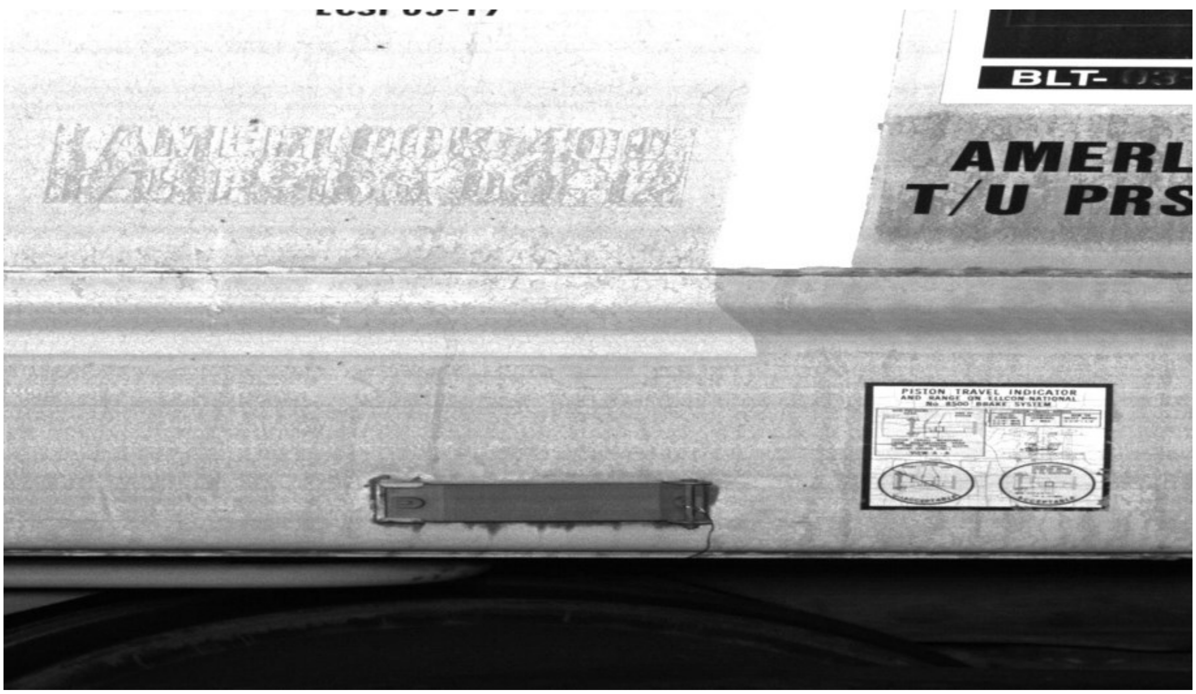


Figure 45. (a) Side sill, (b) cracked side sill with simulated defect (Location-1)

a)



b)

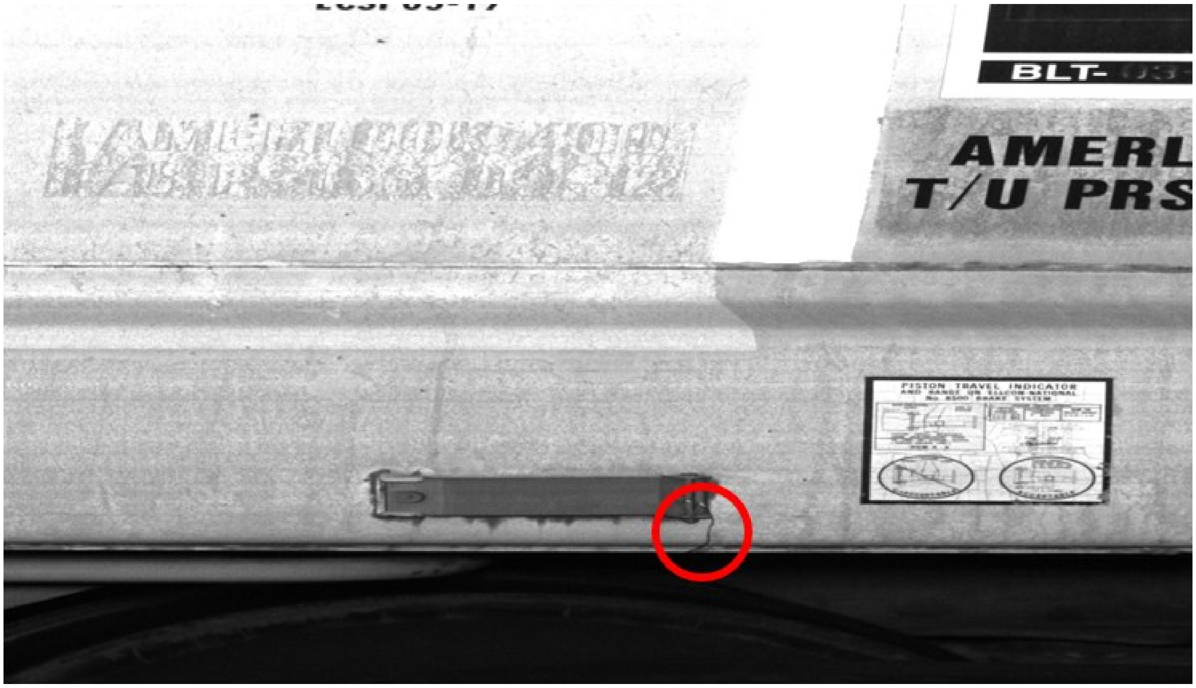
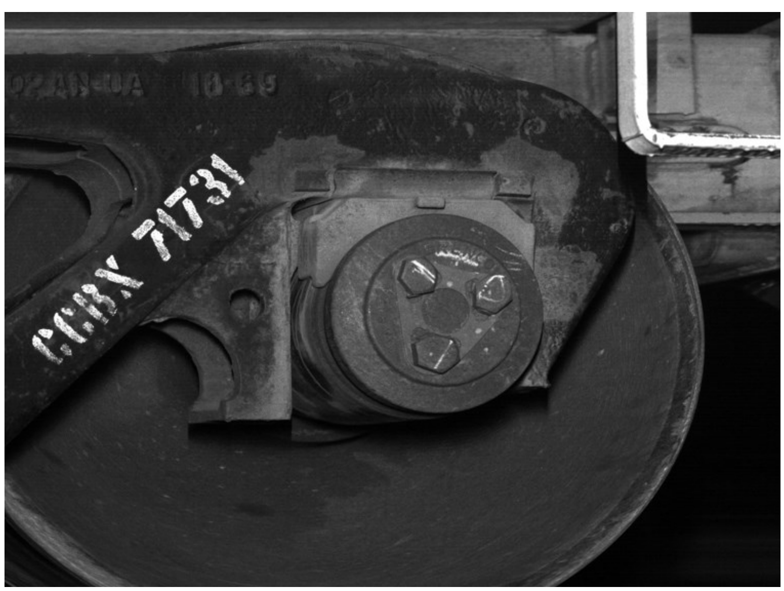


Figure 46. (a) Side sill, (b) cracked side sill with simulated defect (Location-2)

Fake defect 10-Broken step sill

A crack on the step sill was simulated using a metal wire. We wrapped the metal wire around the step sill of the railcar. Figure 48(a) is the obtained image from the TruckView camera system of the TIPS portal. Figure 48(b) shows the location of the simulated broken step sill.

a)



b)

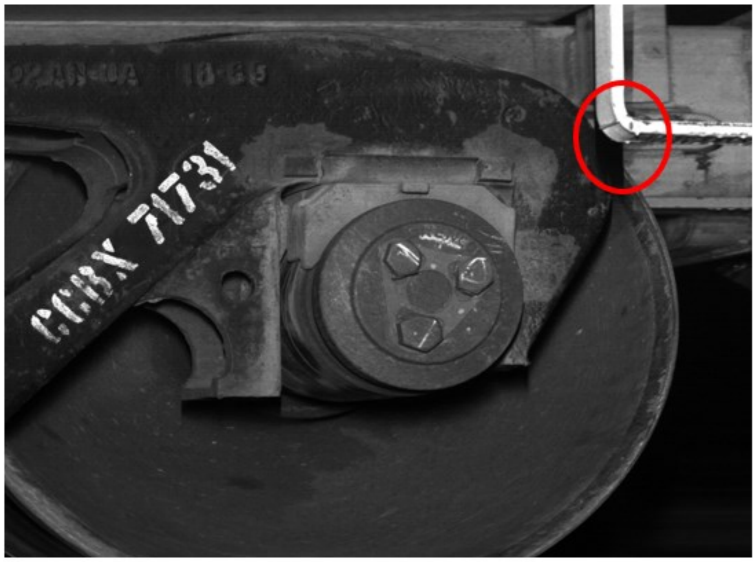


Figure 47. (a) Step sill, (b) cracked step sill with simulated defect

The summary of the results of part 2 is shown in Table 20. These results were generated after the images of both railcars (DOWX20758 and CCBX71731) were inspected by remote CCI as per their inspection routine.

Table 20. Summary of results for part 2

No.	Car ID	Location	Type of defect	Visible in TIPS image (Y/N)	Reported by remote CCI (Y/N)
1	DOWX20758	B-end yoke	Cracked yoke	Yes	Yes
2	DOWX20758	B-end coupler	Cracked coupler	Yes	Yes
3	DOWX20758	B-end right side friction casing	Broken truck spring	No	No
4	CCBX71731	B-end right side casing	Broke truck spring	Yes	No

5	CCBX71731	Beam no-4	Cracked brake beam	No	No
6	CCBX71731	Right side of railcar	Cracked side sill	Yes	No
7	CCBX71731	Right side of railcar	Cracked side sill	Yes	No
8	CCBX71731	A-end right side	Cracked sill step	Yes	No

The data provided in Table 20 shows that the two defects, the broken truck spring on DOWX20758 and cracked brake beam CCBX71731, were not visible in TIPS-obtained images. The possible reason for these two defects could be:

1. Metal wire fell off the railcar part due to the train movement of more than 200 miles.
2. Metal wire used to simulate a broken truck spring might have slipped over the spring coil and gone behind the first row of truck springs.

One of the prior images taken for broke truck spring by the TIPS camera system is shown in Figure-49. It is obvious that when a truck spring breaks, a slight deviation is seen in level, and this trigger the remote CCIs to flag the railcar as having a problem. We could, however, draw the conclusion from comparing the two images (Figures 45(b) and 49) that wrapping metal wire over the spring coil is ineffective in mimicking a broken truck spring problem. It could be the reason why remote CCI missed the broken truck spring defect on CCBX71731 railcar.

The remote CCI successfully identified the two defects, the cracked yoke, and cracked coupler, simulated on DOWX20758. These two defects have a very low frequency of occurrence but impose high risk, thus remote CCIs put enough time and attention on these parts. However, the remaining four defects, cracked side sill (2 locations), cracked sill step, and broken truck spring, were not identified by remote CCI, but these defects were visible in the TIPS obtained images of CCBX71731.

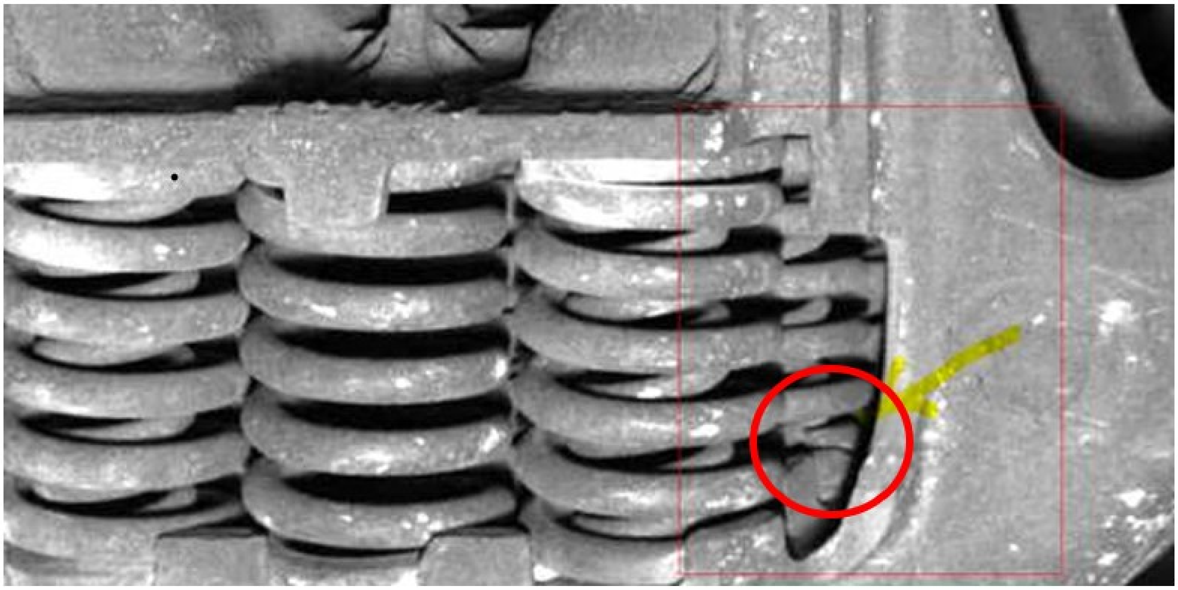


Figure 48. Previously captured broken truck spring in TIPS image.

Based on the inspection of images by remote CCI, it is evident that simulated defects on various components are clearly visible in the images of the TIPS camera system. However, on-duty remote CCI did not identify some of the simulated defects. The possible reasons for three missed defects could be:

1. In case of a cracked side sill, remote CCI may not have seen this defect in the TIPS portal environment, as this defect has a rare frequency of appearance.
2. In case of broken spring and cracked sill step, the simulated defects were not effective enough in replicating real defect and remote CCI considered them as a shadow or foreign material.
3. Remote CCI missed defects due to human error indicate an influence of humans on the quality of remote safety inspection of railcars.

The present results unveil that while all the simulated defects were visible in the images, their ability in imitating a real defect varied. The remote CCIs flagged a few of the simulated defects while inspecting images captured by TIPS. Among the missed cases, the rare frequency defect were not flagged by remote CCIs but frequent defects were rightly flagged.

This study showed that it is feasible to simulate low-frequency defects on railcars. The visibility of these fake defects were examined through the limited number of images. Further simulation is recommended to examine the repeatability of detecting these defects. For some defects, a modified simulation process would also be required.

Recommendations for Improving Human Factor Influence

The number of observations in this study is too small to make any definitive conclusion regarding the effectiveness of the POI, but from the limited observations, it can be concluded that human error in flagging defects affect the quality of the POI. Following are some recommendations to improve human errors in POI:

1. Training: The development of training programs, timely reviewing of training programs, and implementation of a new training program based on employee review are good strategies for boosting the performance of human operators (Shappell & Wiegmann, 2009). All active employees must participate in periodic refresher training programs to keep them updated with safe working conditions and procedures (Kumar & Sinha, 2008). Also, mock/validation tests and simulation training for employees can improve skills and reduce human error in remote inspection technology (Ravindran et al., 2019). In-service training (training that takes place while a person is working and is used to enhance their abilities and skills (What Is In-Service Training, 2022)) is also very helpful in improving the skills of employees during their course of employment. The study conducted in Iran highlighted that in-service training improves the employee's ability and skills and reduces the probability of errors (Saremi & Moein, 2014).

   Provide enough training to remote CCIs for defect identification, especially for defects with a low frequency of occurrence. The railcar inspection with POI technology is a relatively new technology which brings new challenges with it, necessitating employee retraining and more complex training (Kumar & Sinha, 2008). Regular in-service training for employees and continuous upgrading the training resources of POI technology helps in reducing errors and improving the performance of both remote CCI and POI technology.

2. Procedure and checklist: The reliability of operations and error reduction in railway operations are both affected by well-written procedures and job aids (Andersen & Thommesen, 2012). The study of remote control locomotive (RCL) accidents reported poor procedures and practices as major contributors to human error ("Human Error in Railways," 2007). A checklist is a highly valuable document as human memory is not very

reliable, particularly when dealing with stress, exhaustion, and difficult tasks (Winters et al., 2009). The study by Hales & Pronovost (2006) found that checklists are strongly advised tools for error reduction, particularly in industries where human error results are highly disastrous.

For POI technology, well-documented procedures for the inspection of railcars are important for employees to identify defects correctly. One way to help employees distinguish between defects and non-defects is to utilize previously gathered TIPS photographs of various defects and incorporate those images in the procedure or checklist for the employee. (Janota et al., 2022). Also, clear instructions/ checklists about the taxonomy of different defects can help human operators and reduce human error in POI (Patterson & Shappell, 2010).

3. Collaboration and communication: Collaborate with experienced personnel or industry leaders of POI technology and identify improved procedures and best practices. Interaction with supervisors and team members can help in identifying issues and help in reducing human error. Studies of real-world and several simulated emergencies have demonstrated that team communication can significantly detect incorrect plans and errors (Kontogiannis & Malakis, 2009). The study found that briefing is a good way to improve collaboration among the organization's employees and reduces the risk of mistakes. A study in high-risk environments reported that the implementation of briefing as the procedure in their organization showed a drop in errors by 25% (Wahr et al., 2013).

   POI employees help each other in error circumstances by disclosing/communicating their faults and error-prone conditions of the system (Van Dyck et al., 2005). For instance, if an employee is aware of an erroneous condition in the system, then communicates it to the supervisor and other employees a so that they don't use the erroneous system for decision-making. The team needs to create and practice free and open communication since better communication reduces the likelihood of error (Helmreich & Foushee, 2019). The lesson-learned register is one of the best practices for organizations to gather useful information and success or failure. Communicating lesson-learned to the team can reduce the chance of replication of similar mistakes in the future (Jakl et al., 2018).

4. Reduce distraction and workload: There are a few studies that reported that errors in the railway industry increase with the increase in workload, distraction at the workplace, unnecessary discussion, and time pressure of completing the task (Read et al., 2012) (Elsmore & Parasuraman, 2016). The features of work environments, such as noise and lighting, can distract the attention of human operators. Also, working on multiple things simultaneously affects the work efficiency of humans. Thus, minimizing distractions and assigning a manageable workload to employees can reduce the chance of errors (Wall, 2017).

   The use of special types of training, such as sustained attention training (SAT) has shown a reduction in errors compared to others who didn't receive any training. This training helped them maintain their attention for a longer period and reduce mistakes in task completion (Elsmore & Parasuraman, 2016). Prioritization of tasks for the shift and the use of technology/software is one of the techniques used for managing the workload. Also, forecasting the work task before and providing the manpower resources can help in reducing the workload and chances of human error (Martins, 2020).

5. Use of artificial intelligence (AI): There are a few industries where AI-based solutions have been used to detect defects and have proven high detection accuracy by replacing human interventions (Driving Impact at Scale from Automation and AI, 2019). Using supplementary AI-based technology can help increase POI performance by minimizing human errors. When humans are under great stress and fatigue, their performance suffers, which raises the likelihood of committing errors. However, AI is capable of performing high-intensity, repetitive tasks with almost the same accuracy every time, which is not the case for human inspectors (Edwards et al., 2007).

   In the railway industry, AI is used in many complex tasks such as defect/fault detection, maintenance planning, failure prediction, etc. AI is mostly used to make decisions and deal with uncertainty, which lowers the likelihood of human error (Tang et al., 2022). In the case of POI technology inspection, AI-based technology can be used in combination with a human inspection to detect defects/faults in different components of railcars. While AI-based technology undoubtedly reduces human error, it also necessitates intensive training of AI models in order to learn from photos of diverse flaws and defects and verify the precision of defect detection technology (Tang et al., 2022).

Conclusion

The collaboration between the CPR, NRC, TC, and the U of A has provided invaluable insights for simulating the defects on railcars. Keeping track of all the AMVIS defects during the AMVIS project's tenure was quite challenging. Hence, we performed simulated defects for assessing the POI technology for low frequency defects.

We used metal wire, magnets, and silicon caulk for artificial defects on railcar components, and the results depicted that simulation of defects on the railcar components is a viable method for assessing visibility of low-frequency defects such as cracked wheel, cracked center sill and side sill. Although the simulated crack on wheel was not applied on railcar that passed through TIPS due to operational challenge, the statical test shows the potential of applying the simulation method to assess the detectability for this critical yet rarely happened defect.

The experiment on railcar that passed through TIPS covered a few defects such as cracked truck springs, cracked side sill, cracked yoke, cracked couplers, and cracked step sill. All of these simulated defects were visible in the images obtained from the TIPS camera system, which shows the TIPS is effective at capturing these simulated defects. Remote CCI missed the simulated side sill cracks and brake beam crack that rarely happened for the potash train cars. The broken truck spring defect is not as effectively simulated as actual broken truck spring and it was missed by remote CCI. However, remote CCI flagged broken yoke and broken coupler successfully. These results demonstrates that simulated defect method can be used to evaluate the repeatability of RSI if the operation conditions allow the railcars with fake defects being kept in in-service train. For the low frequency and high-risk defects such as crack wheel and center sill, this provides a feasible method to assess their detectability by the technology. Further test using the developed method for such low frequency and high-risk defects is recommended.

The analysis has highlighted that the performance of humans is one of the critical factors that can affect the performance of POI technology. The efforts to strengthen human performance and reduce human error are important for enhancing technical performance and flagging railcar defects. We recommend reducing human error by providing enough training on various defects, training well-written documents, collaborating with industry experts, and reducing operators' workloads. Furthermore, the use of AI-based technology can potentially help human inspection and boost POI technology's performance.

If a large set of data can be collected, the images of simulated defects can be vital in training the AI-based machine learning algorithms, especially for those rare frequency defects.

Chapter 6: Conclusion and Future Studies Suggestions

6.1 Conclusion

The operation of railway network of Canada is one of the important contributors to national economy and its safety is one of the challenges due to various changes associated with season, terrain etc. Over the years, traffic on the railway network is increasing which also contributed to increasing number of accidents such as derailments, HRGC accidents, trespassing etc. The 2018 *Railway Safety Act* review have highlighted the two concerns: 1) accidents and fatalities at HRGCs have increased despite several implementations of safety measures, funding, and initiatives; 2) Incorporating technological solutions for improving safety in railways.

The findings of the first study of this research have unveiled causal factors which affect the safety of HRGCs using ML algorithms. Also, the hotspot analysis and recommendations provided for causal factors are useful for the authorities to concentrate the efforts and budget. The next three studies were about the inspection of railcar component defects using cutting-edge technology which is called POI technology. Various assessment studies were conducted for POI technology in order to evaluate the technology for remote inspection purpose. The second study of the research has reported the high-risk failure causes that affect the reliable operation of TIPS by applying fuzzy-FMEA technique. This study has helped the organizations to locate the high-risk causes in early stage and implement countermeasures for reducing the failure risk. The third study of this research has revealed the underlying causes of human error in remote inspection task using HFACS framework. The findings of the study have shown that "Precondition of Unsafe Act" is most influencing theme for human error in POI technology. The suggested recommendations can help to minimize the frequency of human errors and improve human performance. The last study of artificial defects to find the response of CCI to rare defects. The study has also supported that human error affects the flagging of defects through POI technology. This study has shown promising results for the AI-ML based solution of remote inspection task.

The entire thesis is concentrated on the prevailing concerns of the Canadian railway network and tried to provide the solutions using the machine learning techniques and fundamentals of risk assessment techniques. The findings of the research is helpful for the improving the safety of HRGCs and implementing the technologies for safer, faster and reliable operations of Canadian railways.

6.2 Future studies suggestions

The current research studies of this thesis have identified some limitations. Rectifying these limitations in the future studied could help in better decision making for safety of HRGCs and POI technology. Following are the suggestions for the future studies:

1. Reduce reporting bias and enhance data collection: The HRGC datasets used for analysis exhibit bias due to the reporting process, where accidents are reported by individuals within the railway organization, such as supervisors or conductors. This manual entry of details introduces various factors that contribute to the bias, including the experience of the reporting individual, the level of detail they possess about the accident, and the accuracy of the reported information. These discrepancies contribute to the inherent bias present in the dataset.

   The results of the conducted studies could have highlighted some important factors of the datasets have been reported with other features. Features such as crossing angle, gradient, sightline distance for vehicle at HRGC, distance to nearest intersection, condition of road at accident, visibility, temperature at condition, signs at crossings, number of occupants in vehicle, and train speed at vehicle hit can be very useful in analyzing the safety of HRGCs. Furthermore, the timing of activating the active protection devices at HRGC (Highway-Rail Grade Crossing) plays a crucial role in the analysis. This is because goods trains typically move at slower speeds compared to passenger trains, yet the activating sensor detects the presence of any train and triggers the HRGC system. This discrepancy in train speeds can result in delays for highway traffic, causing anxiety among vehicle drivers who may attempt to cross the HRGC in risky situations. Furthermore, human factors can also be assessed by incorporating features such as driver's condition, driver's experience into the dataset which can unveil the human factor contribution to HRGC accidents.

   Furthermore, a significant number of accidents were not reported with complete information, resulting in empty cells within the dataset. If the reporting process had been more consistent throughout the dataset, it would have facilitated a more comprehensive assessment of HRGC safety.

2. Regular re-evaluation: To ensure accurate risk assessment of POI technology, regular re-assessments should be conducted to identify any new risks arising from changing conditions in the

future. Furthermore, it is essential to establish new measures to address newly identified causes of risk.

3. Innovative practices: In the context of artificial defect simulation, it is crucial to explore innovative approaches for simulating rare defects, such as cracked wheels and cracked axles. Identifying new practices specific to these defects will enhance the simulation process and help in utilizing them for training AI-ML model.

List of References

A study of the role of human factors in railway occurrences and possible mitigation strategies. (2007).

Abdelgawad, M., & Fayek, A. R. (2010). Risk Management in the Construction Industry Using Combined Fuzzy FMEA and Fuzzy AHP. Journal of Construction Engineering and Management, 136(9), 1028–1036. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000210

Adil, O., Ali, A., Ali, M., Ali, A. Y., & Sumait, B. S. (2015). Comparison between the Effects of Different Types of Membership Functions on Fuzzy Logic Controller Performance Controller Performance. International Journal of Emerging Engineering Research and Technology, 3, 76. https://www.researchgate.net/publication/282506091

Afolalu, A. S., Enesi, Y. S., Kehinde, O., Samuel, U. A., Ikechi, V. I., & Remilekun, R. E. (2018). Failure Mode and Effect Analysis a Tool for Reliability Evaluation: Review. European Journal of Engineering Research and Science, 3(4), 65. https://doi.org/10.24018/ejers.2018.3.4.636

Agboola, M. G., Ibidunni, S., & Agboola, M. (2013). Organizational Culture: Creating, Changing, Measuring and Consolidating for Performance. European Journal of Business and Management Www.Iiste.Org ISSN, 5(32), 177–186. https://www.researchgate.net/publication/317605448

Ahmad, M. (1997). Human Resource Management Practices in Indian Railways. Department of Commerce Aligarh Muslim University.

Ahuja, N., & Barkan, C. (2007). Machine vision for railroad equipment undercarriage inspection using multi-spectral imaging. https://railtec.illinois.edu/wp/wp-content/uploads/pdf-archive/Machine-Vision-for-Railroad-Equipment-Undercarriage-Inspection-Using-MultiSpectral-Imaging-HSR-49-Final-Report.pdf

Ajayi, A., Oyedele, L., Owolabi, H., Akinade, O., Bilal, M., Davila Delgado, J. M., & Akanbi, L. (2020). Deep Learning Models for Health and Safety Risk Prediction in Power Infrastructure Projects. Risk Analysis, 40(10), 2019–2039. https://doi.org/10.1111/RISA.13425

Akbari, M., Khazaee, P., Sabetghadam, I., & Karimifard, P. (2013). Failure modes and effects analysis (FMEA) for power transformers. 28th International Power System Conference. https://www.researchgate.net/publication/324818642

An end-to-end guide to understand the math behind XGBoost. (2020). Analytics Vidhya. https://www.analyticsvidhya.com/blog/2018/09/an-end-to-end-guide-to-understand-the-math-behind-xgboost/

An, T. K., & Kim, M. H. (2010). A new Diverse AdaBoost classifier. Proceedings - International Conference on Artificial Intelligence and Computational Intelligence, AICI 2010, 1, 359–363. https://doi.org/10.1109/AICI.2010.82

Andersen, H. B., & Thommesen, J. (2012). Human Error Probabilites (HEPs) for generic tasks and Performance Shaping Factors (PSFs) selected for railway operations. https://backend.orbit.dtu.dk/ws/portalfiles/portal/10626190/Report_on_HRA_for_Banedanmark_v_2_02_Final_Issue.pdf

Arya, M., Sastry G, H., Motwani, A., Kumar, S., & Zaguia, A. (2022). A Novel Extra Tree Ensemble Optimized DL Framework (ETEODL) for Early Detection of Diabetes. Frontiers in Public Health, 9. https://doi.org/10.3389/fpubh.2021.797877

Balaraju, J., Govinda Raj, M., & Murthy, C. S. (2019). Fuzzy-FMEA risk evaluation approach for LHD machine-A case study. Journal of Sustainable Mining, 18(4), 257–268. https://doi.org/10.1016/J.JSM.2019.08.002

Baysari, M. T., Caponecchia, C., McIntosh, A. S., & Wilson, J. R. (2009). Classification of errors contributing to rail incidents and accidents: A comparison of two human error identification techniques. Safety Science, 47(7), 948–957. https://doi.org/10.1016/j.ssci.2008.09.012

Baysari, M. T., McIntosh, A. S., & Wilson, J. R. (2008). Understanding the human factors contribution to railway accidents and incidents in Australia. Accident; Analysis and Prevention, 40(5), 1750–1757. https://doi.org/10.1016/J.AAP.2008.06.013

Benabid, R., Merrouche, D., Bourenane, A., & Alzbutas, R. (2019). Reliability Assessment of Redundant Electrical Power Supply Systems using Fault Tree Analysis, Reliability Block Diagram, and Monte Carlo Simulation Methods. Proceedings of 2018 3rd International

Conference on Electrical Sciences and Technologies in Maghreb, CISTEM 2018. https://doi.org/10.1109/CISTEM.2018.8613431

Best Ways to Motivate Employees to Become More Safety Conscious. (2022). EHS Insight Resources. https://www.ehsinsight.com/blog/best-ways-to-motivate-employees-to-become-more-safety-conscious

Bickley, S. J., & Torgler, B. (2021). A systematic approach to public health – Novel application of the human factors analysis and classification system to public health and COVID-19. Safety Science, 140. https://doi.org/10.1016/J.SSCI.2021.105312

Blagojevi, A., Kasalica, S., Stevi, Ž., Tričkovi, G., & Pavelki, V. (2021). Evaluation of Safety Degree at Railway Crossings in Order to Achieve Sustainable Traffic Management: A Novel Integrated Fuzzy MCDM Model. Sustainability, 13, 832. https://doi.org/10.3390/su13020832

Boyatzis, & E, Richard. (1997). Transforming qualitative information: Thematic analysis and code development. In Sage Publications, Inc. https://psycnet.apa.org/record/1998-08155-000

Brabb, D. C., Vithani, A., & Martin, K. (2017). In-Depth Data Analysis of Grade Crossing Accidents Resulting in Injuries and Fatalities. https://railroads.dot.gov/elibrary/depth-data-analysis-grade-crossing-accidents-resulting-injuries-and-fatalities

Brod, D., & Gillen, D. (2020). A New Model for Highway-Rail Grade Crossing Accident Prediction and Severity. https://railroads.dot.gov/elibrary/new-model-highway-rail-grade-crossing-accident-prediction-and-severity

C, L. (2021). Introduction to Fuzzy Operations. Section. https://www.section.io/engineering-education/fuzzy-logic-operations/

Canada's Freight Railways: Moving the Economy. (2023). Railway Association of Canada. https://www.railcan.ca/101/canadas-freight-railways-moving-the-economy/

CCTV 101: Camera Power Explained - Clinton Electronics. (2023). Clinton Electronics. https://www.clintonelectronics.com/cctv-101-camera-power-explained/

Celik, M., & Cebi, S. (2009). Analytical HFACS for investigating human errors in shipping accidents. Accident Analysis & Prevention, 41(1), 66–75. https://doi.org/10.1016/J.AAP.2008.09.004

Center of Gravity (CoG) method for defuzzification. (2023). CodeCrucks. https://codecrucks.com/center-of-gravity-method-for-defuzzification/

Chadwick, S. G., Zhou, N., & Saat, R. (2014). Highway-rail grade crossing safety challenges for shared operations of high-speed passenger and heavy freight rail in the U.S. Safety Science, 68, 128–137. https://doi.org/10.1016/j.ssci.2014.03.003

Chen, L. (2019). Basic Ensemble Learning (Random Forest, AdaBoost, Gradient Boosting)-Step by Step Explained. Medium. https://towardsdatascience.com/basic-ensemble-learning-random-forest-adaboost-gradient-boosting-step-by-step-explained-95d49d1e2725

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 13-17-August-2016, 785–794. https://doi.org/10.1145/2939672.2939785

Chin, K. S., Wang, Y. M., Ka Kwai Poon, G., & Yang, J. B. (2009). Failure mode and effects analysis using a group-based evidential reasoning approach. Computers and Operations Research, 36(6), 1768–1779. https://doi.org/10.1016/J.COR.2008.05.002

Choosing A Power Distribution Unit. (2021). CyberPower. https://www.cyberpowersystems.com/resources/choosing-a-power-distribution-unit-pdu/

Chorev, S. (2021). A Practical Guide to Data Cleaning | Deepchecks. Deepchecks. https://deepchecks.com/what-is-data-cleaning/

Dadashi, N., Wilson, J. R., Golightly, D., & Sharples, S. (2014). A framework to support human factors of automation in railway intelligent infrastructure. Ergonomics, 57(3), 387–402. https://doi.org/10.1080/00140139.2014.893026

Das, S., Kong, X., Lavrenz, S. M., Wu, L., & Jalayer, M. (2022). Fatal crashes at highway rail grade crossings: A U.S. based study. International Journal of Transportation Science and Technology, 11(1), 107–117. https://doi.org/10.1016/J.IJTST.2021.03.002

Dataset from January 1983 - Transportation Safety Board of Canada. (2020). Transportation Safety Board of Canada. https://www.bst-tsb.gc.ca/eng/stats/rail/data-5.html

de Fabio, F., & Petrillo, A. (2011). Methodological Approach for Performing Human Reliability and Error Analysis in Railway Transportation System. International Journal of Engineering and Technology, 3(5), 341–353.

Defuzzify membership function - MATLAB defuzz. (2023). Mathworks. https://www.mathworks.com/help/fuzzy/defuzz.html

Dernoncourt, F. (2013). Introduction to fuzzy logic.

Dezhkam, B., & Eslami, S. M. (2021). A review of methods for highway-railway crossings safety management process. International Electronic Journal of Mathematics Education, 12(3), 561–568. https://doi.org/10.29333/IEJME/632

Ding, Y., Ying, H., & Shao, S. (2000). Necessary conditions on minimal system configuration for general MISO Mamdani fuzzy systems as universal approximators. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 30(6), 857–864. https://doi.org/10.1109/3477.891147

Drainage Maintenance. (2017). In Loram. www.loram.com

Driving impact at scale from automation and AI. (2019). https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/Driving%20impact%20at%20scale%20from%20automation%20and%20AI/Driving-impact-at-scale-from-automation-and-AI.ashx

Ebrahemzadih, M., Halvani, G. H., Shahmoradi, B., & Giahi, O. (2014). Assessment and Risk Management of Potential Hazards by Failure Modes and Effect Analysis (FMEA) Method in Yazd Steel Complex. Open Journal of Safety Science and Technology, 04(03), 127–135. https://doi.org/10.4236/OJSST.2014.43014

Ebrahimi, H., Sattari, F., Lefsrud, L., & Macciotta, R. (2021). Analysis of train derailments and collisions to identify leading causes of loss incidents in rail transport of dangerous goods in Canada. Journal of Loss Prevention in the Process Industries, 72, 104517. https://doi.org/10.1016/J.JLP.2021.104517

Edwards, R., Hart, J., Todorovic, S., Barkan, C., Ahuja, N., Chua, Z., Kocher, N., & Zeman, J. (2007). Development of Machine Vision Technology for Railcar Safety Appliance Inspection. The International Heavy Haul Conference Specialist Technical Session-High Tech in Heavy Haul, 745–752.

Elsmore, G., & Parasuraman, R. (2016). Reducing Major Rule Violations in Commuter Rail Operations: Distraction and Its Mitigation with Sustained Attention Training. In FRA. https://railroads.dot.gov/elibrary/reducing-major-rule-violations-commuter-rail-operations-distraction-and-its-mitigation

Engineering Track Maintenance Field Handbook. (2022). In Union Pacific. https://www.up.com/emp/engineering/mapcontent/fieldhandbook/Complete%20Book/Redacted%20Track%20Maintenance%20Field%20Handbook.pdf

Enhancing Rail Safety in Canada: Working Together for Safer Communities. (2018). Transport Canada. www.tc.gc.ca/eng/crown-copyright-request-614.html

Ergai, A., Cohen, T., Sharp, J., science, D. W.-S., & 2016, undefined. (2016). Assessment of the Human Factors Analysis and Classification System (HFACS): Intra-rater and inter-rater reliability. Safety Science, 82, 393–398. https://www.sciencedirect.com/science/article/pii/S092575351500257X

Farhanah, D. (2020). MAINTENANCE TASK DETERMINATION OF ENGINE DUMP TRUCK COMPONENT USING RELIABILITY CENTERED MAINTENANCE (RCM) AND FUZZY-FMEA METHOD.

Feili, H. R., Akar, N., Lotfizadeh, H., Bairampour, M., & Nasiri, S. (2013). Risk analysis of geothermal power plants using Failure Modes and Effects Analysis (FMEA) technique. Energy Conversion and Management, 72, 69–76. https://doi.org/10.1016/J.ENCONMAN.2012.10.027

Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating Rigor Using Thematic Analysis: A Hybrid Approach of Inductive and Deductive Coding and Theme Development. International Journal of Qualitative Methods, 5(1). http://www.ualberta.ca/~iiqm/backissues/5_1/pdf/fereday.pdf

Fiber Optic Cables Cuts: Most Common Causes & How To Combat Them. (2023). Commercial Electronics. https://www.commercialelectronics.com/fiber-optic-cables-cut/

Fuzzy Logic Fundamentals. (2001).

Geramian, A., Shahin, A., Minaei, B., & Antony, J. (2019). Enhanced FMEA: An integrative approach of fuzzy logic-based FMEA and collective process capability analysis. Https://Doi.Org/10.1080/01605682.2019.1606986, 71(5), 800–812. https://doi.org/10.1080/01605682.2019.1606986

Ghofrani, F., Sun, H., & He, Q. (2022). Analyzing Risk of Service Failures in Heavy Haul Rail Lines: A Hybrid Approach for Imbalanced Data. Risk Analysis, 42(8), 1852–1871. https://doi.org/10.1111/RISA.13694

Goel, A., & Graves, R. J. (2007). Using failure mode effect analysis to increase electronic systems reliability. ISSE 2007 - 30th International Spring Seminar on Electronics Technology 2007; Conference Proceedings: Emerging Technologies for Electronics Packaging, 128–133. https://doi.org/10.1109/ISSE.2007.4432833

Grade Crossings Inventory. (2022). Government of Canada. https://open.canada.ca/data/en/dataset/d0f54727-6c0b-4e5a-aa04-ea1463cf9f4c

Griggs, F. J. (2012). A Human Factors Analysis and Classification System (HFACS) Examination of Commercial Vessel Accidents [NAVAL POSTGRADUATE SCHOOL]. http://hdl.handle.net/10945/17373

Gupta, M., & C, V. (2021). A Study and Analysis of Machine Learning Techniques in Predicting Wine Quality. International Journal of Recent Technology and Engineering (IJRTE), 10(1), 314–319. https://doi.org/10.35940/IJRTE.A5854.0510121

Hadj-Mabrouk, H. (2018). New approach of assessing human errors in railways Contribution of Machine Learning and Ontology to the Prevention of Railway Accidents View project Railway safety directives and regulations View project. Civil Engineering Series. https://doi.org/10.1515/tvsbses-2018-0007

Hale, A. R., Heijer, T., & Koornneef, F. (2003). Management of Safety Rules: The Case of Railways. Safety Science Monitor, 7(1), 1–11.

Hales, B. M., & Pronovost, P. J. (2006). The checklist—a tool for error management and performance improvement. Journal of Critical Care, 21(3), 231–235. https://doi.org/10.1016/J.JCRC.2006.06.002

Handling Imbalanced Data using Python. (2020). Analytic Vidhya. https://www.analyticsvidhya.com/blog/2020/07/10-techniques-to-deal-with-class-imbalance-in-machine-learning/

Handt, K., Griepentrog, G., & Maier, R. (2008). Intelligent, compact and robust semiconductor circuit breaker based on silicon carbide devices. PESC Record - IEEE Annual Power Electronics Specialists Conference, 1586–1591. https://doi.org/10.1109/PESC.2008.4592166

Hao, W., Kamga, C., & Wan, D. (2016). The effect of time of day on driver's injury severity at highway-rail grade crossings in the United States. Journal of Traffic and Transportation Engineering (English Edition), 3(1), 37–50. https://doi.org/10.1016/J.JTTE.2015.10.006

Helmreich, R. L., & Foushee, H. C. (2019). Why CRM? Empirical and Theoretical Bases of Human Factors Training. Crew Resource Management, 3–52. https://doi.org/10.1016/B978-0-12-812995-1.00001-4

Heydari, S., & Fu, L. (2015). Developing safety performance functions for railway grade crossings: A case study of Canada. ASME/IEEE Joint Rail Conference, V001T06A017. https://doi.org/10.1115/JRC2015-5768

Highway-Rail Grade Crossings Overview . (2019). Federal Railroad Administration (FRA). https://railroads.dot.gov/program-areas/highway-rail-grade-crossing/highway-rail-grade-crossings-overview

Hou, Y., Liu, C.-C., Zhang, P., & Sun, K. (2009). Constructing power system restoration strategies. 2009 International Conference on Electrical and Electronics Engineering - ELECO 2009. https://doi.org/10.1109/ELECO.2009.5355208

How Hot Spot Analysis (Getis-Ord Gi*) works—ArcGIS Pro. (2020). Esri. https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/h-how-hot-spot-analysis-getis-ord-gi-spatial-stati.htm

Huang, J., You, J. X., Liu, H. C., & Song, M. S. (2020). Failure mode and effect analysis improvement: A systematic literature review and future research agenda. Reliability Engineering & System Safety, 199, 106885. https://doi.org/10.1016/J.RESS.2020.106885

Hudson, P. T., & van der Graaf, G. (1998). Bending The Rules: Managing Violation in the Workplace. In Society of Petroleum Engineers International Conference on Health, Safety and Environment in Oil and Gas Exploration.

Human Error in Railways. (2007). In Human Reliability and Error in Transportation Systems. Springer. https://doi.org/10.1007/978-1-84628-812-8_6

Human Factors Analysis and Classification System (HFACS). (2023). SKYbrary Aviation Safety. https://www.skybrary.aero/articles/human-factors-analysis-and-classification-system-hfacs

Integrating Human Factors in European Railways Safety Management Systems. (2016). European Union Agency for Railways (ERA).

Isaed, W., & Znaid, A. (2018). Design of lightning and over-voltage protection system for building (B+) at PPU campus.

Ivančan, J., & Lisjak, D. (2021). New FMEA Risks Ranking Approach Utilizing Four Fuzzy Logic Systems. Machines 2021, Vol. 9, Page 292, 9(11), 292. https://doi.org/10.3390/MACHINES9110292

Jafarinodoushan, M., & Abdar, F. T. (2021). Identifying and Prioritizing the Factors Affecting on the Human Errors and Ways to Reduce it in Oil and Gas Industry: Systematic Review. JOURNAL OF CRITICAL REVIEWS, 8(1), 1–9.

Jakl, A., Schöffer, L., Husinsky, M., & Wagner, M. (2018). Augmented Reality for Industry 4.0: Architecture and User Experience. FMT, 38–42.

Janecek, A. G. K., Gansterer, W. N., Demel, M. A., & Ecker, G. F. (2008). On the Relationship Between Feature Selection and Classification Accuracy. JMLR: Workshop and Conference Proceedings 4, 4, 90–105. http://proceedings.mlr.press/v4/janecek08a/janecek08a.pdf

Janota, A., Pirník, R., Ždánsky, J., & Nagy, P. (2022). Human Factor Analysis of the Railway Traffic Operators. Machines, 10(9). https://doi.org/10.3390/machines10090820

Johansson, J., Hassel, H., & Zio, E. (2013). Reliability and vulnerability analyses of critical infrastructures: Comparing two approaches in the context of power systems. Reliability Engineering & System Safety, 120, 27–38. https://doi.org/10.1016/J.RESS.2013.02.027

Jonker, A., Geerts, W. J. C., Chieco, P., Moorman, A. F. M., Lamers, W. H., & Van Noorden, C. J. F. (1997). Basic strategies for valid cytometry using image analysis. Histochemical Journal, 29(5), 347–364. https://doi.org/10.1023/A:1026434816947

Keramati, A., Lu, P., Tolliver, D., & Wang, X. (2020). Geometric effect analysis of highway-rail grade crossing safety performance. Accident Analysis and Prevention, 138, 105470. https://doi.org/10.1016/J.AAP.2020.105470

Khosravanian, R., Sabah, M., Wood, D. A., & Shahryari, A. (2016). Weight on drill bit prediction models: Sugeno-type and Mamdani-type fuzzy inference systems compared. Journal of Natural Gas Science and Engineering, 36, 280–297. https://doi.org/10.1016/J.JNGSE.2016.10.046

Kiger, M. E., & Varpio, L. (2020). Thematic analysis of qualitative data: AMEE Guide No. 131 Thematic analysis of qualitative data: AMEE Guide No. 131. Medical Teacher, 42, 846–854. https://doi.org/10.1080/0142159X.2020.1755030

Kight, H. (2013). Failure Analysis of Thermostats in Temperature Controlled Systems. https://mmengineering.com/wp-content/uploads/2013/10/Conduit-Vol.-13-No.-3.pdf

Kirkire, M. S., Rane, S. B., & Jadhav, J. R. (2015). Risk management in medical product development process using traditional FMEA and fuzzy linguistic approach: A case study. Journal of Industrial Engineering International, 11(4), 595–611. https://doi.org/10.1007/S40092-015-0113-Y/FIGURES/10

Kontogiannis, T., & Malakis, S. (2009). A proactive approach to human error detection and identification in aviation and air traffic control. Safety Science, 47(5), 693–706. https://doi.org/10.1016/J.SSCI.2008.09.007

Kumar, A., & Sinha, P. K. (2008). Human Error Control in Railways. Jordan Journal of Mechanical and Industrial Engineering, 2(4).

Kumru, M., & Kumru, P. Y. (2013). Fuzzy FMEA application to improve purchasing process in a public hospital. Applied Soft Computing Journal, 13(1), 721–733. https://doi.org/10.1016/J.ASOC.2012.08.007

Kurama Vihar. (2020). Introduction to Bagging and Ensemble Methods. PaperspaceBlog. https://blog.paperspace.com/bagging-ensemble-methods/

Kürs, M., Uçar, K., Nour, M., Sindi, H., & Polat, K. (2020). The Effect of Training and Testing Process on Machine Learning in Biomedical Datasets. Mathematical Problems in Engineering, 1–17. https://doi.org/10.1155/2020/2836236

Kwon, O., & Sim, J. M. (2013). Effects of data set features on the performances of classification algorithms. Expert Systems with Applications, 40(5), 1847–1857. https://doi.org/10.1016/j.eswa.2012.09.017

Kyriakidis, M., Majumdar, A., & Ochieng, W. Y. (2018). The human performance railway operational index—a novel approach to assess human performance for railway operations. Reliability Engineering and System Safety, 170, 226–243. https://doi.org/10.1016/J.RESS.2017.10.012

Kyriakidis, M., Pak, K. T., & Majumdar, A. (2015). Railway accidents caused by human error: Historic analysis of UK railways, 1945 to 2012. In Transportation Research Record (Vol. 2476, pp. 126–136). National Research Council. https://doi.org/10.3141/2476-17

Lago, P., Bizzarri, G., Scalzotto, F., Parpaiola, A., Amigoni, A., Putoto, G., & Perilongo, G. (2012). Use of FMEA analysis to reduce risk of errors in prescribing and administering drugs in paediatric wards: A quality improvement report. BMJ Open, 2(6). https://doi.org/10.1136/BMJOPEN-2012-001249

Lakshmi, S., Srikanth, I., & Arockiasamy, M. (2019). Identification of Traffic Accident Hotspots using Geographical Information System (GIS). International Journal of Engineering and Advanced Technology, 9(2), 4429–4438. https://doi.org/10.35940/ijeat.B3848.129219

Łapczyńska, D., & Burduk, A. (2021). Fuzzy FMEA Application to Risk Assessment of Quality Control Process. Advances in Intelligent Systems and Computing, 1268 AISC, 309–319. https://doi.org/10.1007/978-3-030-57802-2_30

Lasisi, A., Li, P., & Chen, J. (2020). Hybrid Machine Learning and Geographic Information Systems Approach — A Case for Grade Crossing Crash Data Analysis. Advances in Data Science and Adaptive Analysis, 12(01), 2050003. https://doi.org/10.1142/S2424922X20500035

Li, J., Li, H., & Yu, J. L. (2011). Application of Random-SMOTE on imbalanced data mining. Proceedings - 2011 4th International Conference on Business Intelligence and Financial Engineering, BIFE 2011, 130–133. https://doi.org/10.1109/BIFE.2011.25

Li, Y., & Liang, C. (2018). The Analysis of Spatial Pattern and Hotspots of Aviation Accident and Ranking the Potential Risk Airports Based on GIS Platform. Journal of Advanced Transportation, 2018. https://doi.org/10.1155/2018/4027498

Liang, D., & Li, F. (2021). Risk Assessment in Failure Mode and Effect Analysis: Improved ORESTE Method With Hesitant Pythagorean Fuzzy Information. IEEE Transactions on Engineering Management. https://doi.org/10.1109/TEM.2021.3073373

Liu, H. C., Liu, L., & Liu, N. (2013). Risk evaluation approaches in failure mode and effects analysis: A literature review. Expert Systems with Applications, 40(2), 828–838. https://doi.org/10.1016/J.ESWA.2012.08.010

Lu, P., & Tolliver, D. (2016). Accident prediction model for public highway-rail grade crossings. Accident Analysis and Prevention, 90, 73–81. https://doi.org/10.1016/j.aap.2016.02.012

Lu, P., Tolliver, D., & Zheng, Z. (2018). Highway-Rail Grade Crossing Traffic Hazard Forecasting Model. https://www.ugpti.org/resources/reports/downloads/mpc18-354.pdf

Lu, P., Zheng, Z., Ren, Y., Zhou, X., Keramati, A., Tolliver, D., & Huang, Y. (2020). A Gradient Boosting Crash Prediction Approach for Highway-Rail Grade Crossing Crash Analysis. https://doi.org/10.1155/2020/6751728

M, R. (2019). Confusion matrix- Machine learning | Clairvoyant Blog. Medium. https://blog.clairvoyantsoft.com/churning-the-confusion-out-of-the-confusion-matrix-b74fb806e66

Madigan, R., & Golightly, D. (2016). Application of Human Factors Analysis and Classification System (HFACS) to UK rail safety of the line incidents. Accident Analysis & Prevention, 97, 122–131. https://www.sciencedirect.com/science/article/pii/S0001457516303098?casa_token=jnC76lGkdO8AAAAA:_VCGdrMVoH1_yw5WmKkuH9ZB6MXS32evfCqa31KjVvAiQ5xTPfOMG2JVtSf-i2oyTKeDoU9mvQ

Manoj, S. (2021a). Feature Selection Methods | Feature Selection Techniques in Python. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2021/04/discovering-the-shades-of-feature-selection-methods/

Manoj, S. (2021b). ML | Extra Tree Classifier for Feature Selection - GeeksforGeeks. Analytics Vidhya. https://www.geeksforgeeks.org/ml-extra-tree-classifier-for-feature-selection/

Martin, L. D., Grigg, E. B., Verma, S., Latham, G. J., Rampersad, S. E., & Martin, L. D. (2017). Outcomes of a Failure Mode and Effects Analysis for medication errors in pediatric anesthesia. Paediatric Anaesthesia, 27(6), 571–580. https://doi.org/10.1111/PAN.13136

Martins, J. (2020). How To Effectively Manage Your Team's Workload. https://asana.com/resources/effectively-manage-team-workload

Mendonca, F. A. C., Chenyu, H., Richard, F., & Keller, J. (2017). A CASE STUDY USING THE HUMAN FACTORS ANALYSIS AND CLASSIFICATION SYSTEM FRAMEWORK. In 19th International Symposium on Aviation Psychology, 113–118.

Mental health in the workplace. (2015). Government of Canada. https://www.canada.ca/en/public-health/services/mental-health-workplace.html

Miles, S. B., Jagielo, N., & Gallagher, H. (2016). Hurricane Isaac Power Outage Impacts and Restoration. Journal of Infrastructure Systems, 22(1). https://doi.org/10.1061/(ASCE)IS.1943-555X.0000267

Module 4 - Human Error. (2010). Transport Canada. https://tc.canada.ca/en/aviation/publications/pilot-decision-making-pdm-tp-13897/module-4-human-error

Mohajon, J. (2020). Confusion Matrix for Your Multi-Class Machine Learning Model. Medium. https://towardsdatascience.com/confusion-matrix-for-your-multi-class-machine-learning-model-ff9aa3bf7826

Mok, S. C., & Savage, I. (2005). Why has safety improved at rail-highway grade crossings? Risk Analysis, 25(4), 867–881. https://doi.org/10.1111/J.1539-6924.2005.00642.X

Morgan, Abbott, Furness, & Ramsay. (2016). UK rail workers' perceptions of accident risk factors: An exploratory study. International Journal of Industrial Ergonomics, 55, 103–113. https://doi.org/10.1016/j.ergon.2016.08.003

Mulugeta Tola, A., & Gebissa, A. (2019). Identifying Black Spot Accident Zones using a Geographical Information System on Kombolcha-Dessie Road in Ethiopia. International Journal of Sciences: Basic and Applied Research (IJSBAR) International Journal of Sciences: Basic and Applied Research, 48(1), 66–79. http://gssrr.org/index.php?journal=JournalOfBasicAndApplied

Nikulski, J. (2020). The Ultimate Guide to AdaBoost, random forests and XGBoost. Medium. https://towardsdatascience.com/the-ultimate-guide-to-adaboost-random-forests-and-xgboost-7f9327061c4f

Nkosi, M., Gupta, K., & Mashinini, M. (2020). Causes and Impact of Human Error in Maintenance of Mechanical Systems. MATEC Web of Conferences . https://doi.org/10.1051/matecconf/202031205001

Nuchpho, P., Nansaarng, S., & AUD Pongpullponsak, A. (2014). Risk Assessment in the Organization by Using FMEA Innovation: A Literature Review. Proceedings of the 7thInternational Conference on Educational Reform (ICER 2014), 781–789. https://www.researchgate.net/publication/264116818

Okyere, P. Y., & Eduful, G. (2007). Lightning protection of structures and electronic equipment: a case study. International Journal of Applied Engineering Research, 2(1), 1–15. https://go.gale.com/ps/i.do?p=AONE&sw=w&issn=09734562&v=2.1&it=r&id=GALE%7CA172134707&sid=googleScholar&linkaccess=fulltext

Ouedraogo, K. A., Beugin, J., El-Koursi, E. M., Clarhaut, J., Renaux, D., & Lisiecki, F. (2018). Toward an Application Guide for Safety Integrity Level Allocation in Railway Systems. Risk Analysis, 38(8), 1634–1655. https://doi.org/10.1111/RISA.12972

Patterson, J. M., & Shappell, S. A. (2010). Operator error and system deficiencies: Analysis of 508 mining incidents and accidents from Queensland, Australia using HFACS. Accident Analysis and Prevention, 42(4), 1379–1385. https://doi.org/10.1016/J.AAP.2010.02.018

Poddar, S., Panja, S. C., & Gangopadhyaya, M. (2015). Human Factors Analysis for Railway Coach and Bogie Maintenance Using AHP. Proceedings of the 2015 International Conference on Operations Excellence and Service Engineering.

Popescu, V. F., & Pistol, M. S. (2021). Fuzzy logic expert system for evaluating the activity of university teachers. International Journal of Assessment Tools in Education, 8(4), 991–1008. https://doi.org/10.21449/IJATE.1025690

Poranen, A., Kouvonen, A., & Nordquist, H. (2021). Predicting surgical resource consumption and in-hospital mortality in resource-scarce conflict settings: a retrospective study. BMC Emergency Medicine, 22, 178. https://doi.org/10.1186/s12873-022-00738-x

Prasannakumar, V., Vijith, H., Charutha, R., & Geetha, N. (2011). Spatio-temporal clustering of road accidents: GIS based analysis and assessment. Procedia - Social and Behavioral Sciences, 21, 317–325. https://doi.org/10.1016/J.SBSPRO.2011.07.020

Preparing for power loss - IBM Documentation. (2023). IBM. https://www.ibm.com/docs/en/i/7.4?topic=outages-preparing-power-loss

Rachieru, N., Belu, N., & Anghel, D. C. (2014). Evaluating the risk of failure on injection pump using fuzzy FMEA method. Applied Mechanics and Materials, 657, 976–980. https://doi.org/10.4028/WWW.SCIENTIFIC.NET/AMM.657.976

Rafieyan, A., Sarvari, H., & Chan, D. W. M. (2022). Identifying and Evaluating the Essential Factors Affecting the Incidence of Site Accidents Caused by Human Errors in Industrial Parks Construction Projects. International Journal of Environmental Research and Public Health, 19(16). https://doi.org/10.3390/ijerph191610209

Rahimdel, M. J., & Ghodrati, B. (2021). Risk prioritization for failure modes in mining railcars. Sustainability (Switzerland), 13(11). https://doi.org/10.3390/SU13116195

Rail Safety in Canada. (2021). Transport Canada. https://tc.canada.ca/en/rail-transportation/rail-safety-canada

Rail transportation occurrences in 2020. (2020). Transportation Safety Board of Canada. https://www.bst-tsb.gc.ca/eng/stats/rail/2020/sser-ssro-2020.html#3.0

Rail transportation occurrences in 2021. (2021). Transportation Safety Board of Canada (TSB). http://www.tsb.gc.ca/eng/stats/rail/2021/sser-ssro-2021.html

Railcar Inspection Portal. (2022). Duos Technologies, Inc. https://www.duostechnologies.com/railcar-inspection-portal/

Railroad Track Facts… Construction, Safety and More. (2022). SafeRacks. https://www.saferack.com/railroad-track-facts-construction-safety/

Ravindran, S., Thomas-Gibson, S., Murray, S., & Wood, E. (2019). Improving safety and reducing error in endoscopy: Simulation training in human factors. Frontline Gastroenterology, 10(2), 160–166. https://doi.org/10.1136/FLGASTRO-2018-101078

Read, G. J. M., Lenné, M. G., & Moss, S. A. (2012). Associations between task, training and social environmental factors and error types involved in rail incidents and accidents. Accident Analysis and Prevention, 48, 416–422. https://doi.org/10.1016/J.AAP.2012.02.014

Reducing Errors and Improving Safety Through a Human-Performance Initiative. (2023). Journal of Petroleum Technology. https://jpt.spe.org/reducing-errors-and-improving-safety-through-a-human-performance-initiative

Reduction of speed limit at approaches to railway level crossings in WA. - Australasian College of Road Safety. (n.d.). Retrieved November 5, 2022, from https://acrs.org.au/article/reduction-of-speed-limit-at-approaches-to-railway-level-crossings-in-wa/

Reinach, S., & Viale, A. (2006). Application of a human error framework to conduct train accident/incident investigations. Accident Analysis and Prevention, 38, 396–406. https://doi.org/10.1016/j.aap.2005.10.013

Report on Railway Safety and Interoperability in the EU - 2022. (2022). https://doi.org/10.2821/060591

Riza, L. S., Bergmeir, C., Herrera, F., & Manuel Benítez, J. (2019). A Universal Representation Framework for Fuzzy Rule-Based Systems Based on PMML.

Rizvi, S., Mitchell, J., Razaque, A., Rizvi, M. R., & Williams, I. (2020). A fuzzy inference system (FIS) to evaluate the security readiness of cloud service providers. Journal of Cloud Computing, 9(1), 1–17. https://doi.org/10.1186/S13677-020-00192-9/FIGURES/8

Roberts, K., Dowell, A., & Nie, J. B. (2019). Attempting rigour and replicability in thematic analysis of qualitative research data; A case study of codebook development. BMC Medical Research Methodology, 19(1). https://doi.org/10.1186/S12874-019-0707-Y

Robertson, O. (2014). Gender and crew resource management: A phenomenological qualitative study. University of Phoenix.

Rothblum, A. M. (2020). Human Error and Marine Safety. https://bowles-langley.com/wp-content/files_mf/humanerrorandmarinesafety26.pdf

S, P., & Dhenakaran, S. (2016). Comparison of Triangular and Trapezoidal Fuzzy Membership Function. Journal of Computer Science and Engineering , 2(8), 46–51.

Salas, E. (2022). Rail industry in Canada - statistics & facts | Statista. https://www.statista.com/topics/5062/rail-industry-in-canada/#dossierKeyfigures

Salvaraji, L., Jeffree, M. S., Lukman, K. A., & Saupin, S. (2022). Electrical safety in hospital setting: A narrative review. https://doi.org/10.1016/j.amsu.2022.103781

Saremi, H., & Moein, B. (2014). Study of Correlation Between Short-term In-Service Training Courses to Employee Empowerment (Case study: Islamic Azad University- Quhan branch). Indian Journal of Scientific Research, 4(3), 302–310. https://www.researchgate.net/publication/272176580

Sawadisavi, S., Edwards, J. R., Resendiz, E., & Hart, J. M. (2009). Machine-Vision Inspection of Railroad Track. TRB 88th Annual Meeting.

Scarborough, A., Bailey, L., & Pounds, J. (2005). Examining ATC Operational Errors Using the Human Factors Analysis and Classification System Final Report.

Sekasi, J., & Solihu, H. (2021). Safety and risk analysis at railway crossings of north-south Addis Ababa light rail. Smart and Resilient Transportation, 3(3), 266–282. https://doi.org/10.1108/SRT-08-2021-0007

Shappell, S. A., & Wiegmann, D. A. (2000). The Human Factors Analysis and Classification System-HFACS.

Shappell, S., & Wiegmann, D. (2009). A Methodology for Assessing Safety Programs Targeting Human Error in Aviation. THE INTERNATIONAL JOURNAL OF AVIATION PSYCHOLOGY, 19(3), 252–269. https://doi.org/10.1080/10508410902983904

Sharma, R. K., Kumar, D., & Kumar, P. (2005). Systematic failure mode effect analysis (FMEA) using fuzzy linguistic modelling. International Journal of Quality and Reliability Management, 22(9), 986–1004. https://doi.org/10.1108/02656710510625248

Sifwat, Y., Hameed, M., Ahsan, E., & Ahmed, W. (2021). Application of Fuzzy FMEA to assess non-technical risks linked to a power station's operations. Proceedings of 1st International Conference on Business, Management & Social Sciences (ICBMASS). https://ssrn.com/abstract=3916897

Silla, A., & Kallberg, V. P. (2012). The development of railway safety in Finland. Accident Analysis & Prevention, 45, 737–744. https://doi.org/10.1016/J.AAP.2011.09.043

Singh, J., Singh, H., & Singh, B. (2020). Fuzzy-based FMEA – Application. Prioritization of Failure Modes in Manufacturing Processes, 61–94. https://doi.org/10.1108/978-1-83982-142-420201003

Singh, P., Pasha, J., Khorram-Manesh, A., Goniewicz, K., Roshani, A., & Dulebenets, M. A. (2021). A holistic analysis of train-vehicle accidents at highway-rail grade crossings in Florida. Sustainability (Switzerland), 13(16), 105236. https://doi.org/10.3390/su13168842

Singh, S., Majumdar, A., & Kyriakidis, M. (2017). Incorporating Human Reliability Analysis to enhance Maintenance Audits: The Case of Rail Bogie Maintenance. International Journal of Prognostics and Health Management, 8(3), 62.

Soleimani, S., Leitner, M., & Codjoe, J. (2021). Applying machine learning, text mining, and spatial analysis techniques to develop a highway-railroad grade crossing consolidation model. Accident Analysis and Prevention, 152, 105985. https://doi.org/10.1016/J.AAP.2021.105985

Spatial Autocorrelation (Global Moran's I) (Spatial Statistics)—ArcGIS Pro. (2020). Esri. https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/spatial-autocorrelation.htm

Stojković, T., Marinković, V., Jaehde, U., & Manser, T. (2017). Using Failure mode and Effects Analysis to reduce patient safety risks related to the dispensing process in the community pharmacy setting. Research in Social and Administrative Pharmacy, 13(6), 1159–1166. https://doi.org/10.1016/J.SAPHARM.2016.11.009

Strategies for increasing system availability. (2001). Cabling Installation & Maintenance. https://www.cablinginstall.com/home/article/16466101/strategies-for-increasing-system-availability

T, M., & K, M. (2016). Human Resource Management Practices In Railway-A Review Study. Indian Journal of Applied Research, 669(7).

Tang, R., De Donato, L., Besinovic, N., Flammini, F., & Goverde, R. M. (2022). A literature review of Artificial Intelligence applications in railway systems. Transportation Research Part C:Emerging Technologies, 140, 103679. https://doi.org/10.1016/j.trc.2022.103679

Tang, R., de Donato, L., Bešinović, N., Flammini, F., Goverde, R. M. P., Lin, Z., Liu, R., Tang, T., Vittorini, V., & Wang, Z. (2022). A literature review of Artificial Intelligence applications in railway systems. Transportation Research Part C: Emerging Technologies, 140. https://doi.org/10.1016/j.trc.2022.103679

Tanha, J., Abdi, Y., Samadi, N., Razzaghi, N., & Asadpour, M. (2020). Boosting methods for multi-class imbalanced data classification: an experimental review. Journal of Big Data, 7(1), 1–47. https://doi.org/10.1186/S40537-020-00349-Y/FIGURES/5

Tay, K. M., & Lim, C. P. (2006). Fuzzy FMEA with a guided rules reduction system for prioritization of failures. International Journal of Quality and Reliability Management, 23(8), 1047–1066. https://doi.org/10.1108/02656710610688202

Tenney, M. (2022). How To Manage Organizational Culture (11 Essential Steps). Business Leadership Today. https://businessleadershiptoday.com/how-do-you-manage-organizational-culture/

Tey, L. S., Wallis, G., Cloete, S., & Ferreira, L. (2013). Modelling driver behaviour towards innovative warning devices at railway level crossings. Accident Analysis and Prevention, 51, 104–111. https://doi.org/10.1016/j.aap.2012.11.002

Thakore, R., Dave, R., & Parsana, T. (2015). A Case Study: A Process FMEA Tool to Enhance Quality and Efficiency of Bearing Manufacturing Industry. Scholars Journal of Engineering and Technology, 3(SJET), 413–418. www.saspublisher.com

The HFACS Framework. (2014). Hfacs.Inc. https://hfacs.com/hfacs-framework.html

The importance of human factors in the rail industry. (2021). Leedeo Engineering 2020. https://www.leedeo.es/l/human-factors-railway/

Van Dyck, C., Baer, M., Frese, M., & Sonnentag, S. (2005). Organizational error management culture and its impact on performance: A two-study replication. Journal of Applied Psychology, 90(6), 1228–1240. https://doi.org/10.1037/0021-9010.90.6.1228

Vertiv. (2016). Consideration For A Highly Available Intelligent Rack Power Distribution Unit. https://www.vertiv.com/495a84/globalassets/products/critical-power/power-distribution/considerations-for-a-highly-available-intelligent-rack-power-distribution-unit-.pdf

Vijaya, J., & Sivasankar, E. (2018). Computing efficient features using rough set theory combined with ensemble classification techniques to improve the customer churn prediction in telecommunication sector. Computing, 100(8), 839–860. https://doi.org/10.1007/S00607-018-0633-6

Wahr, J. A., Prager, R. L., Abernathy, J. H., Martinez, E. A., Salas, E., Seifert, P. C., Groom, R. C., Spiess, B. D., Searles, B. E., Sundt, T. M., Sanchez, J. A., Shappell, S. A., Culig, M. H., Lazzara, E. H., Fitzgerald, D. C., Thourani, V. H., Eghtesady, P., Ikonomidis, J. S., England, M. R., … Nussmeier, N. A. (2013). Patient Safety in the Cardiac Operating Room: Human Factors and Teamwork. Circulation, 128(10), 1139–1169. https://doi.org/10.1161/CIR.0B013E3182A38EFA

Wall, M. (2017). Human Factors guidance to improve reliability of non-Destructive testing in the Offshore Oil and Gas Industry. www.hois.co.uk

Wang, C. (2015). A Study of Membership Functions on Mamdani-Type Fuzzy Inference System for Industrial Decision-Making. http://preserve.lehigh.edu/etd

Wei, Q., & Dunbrack, R. L. (2013). The role of balanced training and testing data sets for binary classifiers in bioinformatics. PloS One, 8(7). https://doi.org/10.1371/JOURNAL.PONE.0067863

What is Human Factors and Ergonomics. (2022). Human Factors and Ergonomics Society. https://www.hfes.org/About-HFES/What-is-Human-Factors-and-Ergonomics

What is In-Service Training. (2022). IGI Global. https://www.igi-global.com/dictionary/in-service-training/58178

What is the 80 rule in electrical? (2023). https://www.calendar-canada.ca/faq/what-is-the-80-rule-in-electrical

What You Need To Know About AC Thermostat Calibration. (2021). One Stop Heating & Cooling. https://onestopheatingandcooling.us/what-you-need-to-know-about-ac-thermostat-calibration/

Wiegmann, D., Faaborg, T., Boquet, A., Detwiler, C., Holcomb, K., & Shappell, S. (2005). Human Error and General Aviation Accidents: A Comprehensive, Fine-Grained Analysis Using HFACS.

Winters, B. D., Gurses, A. P., Lehmann, H., Sexton, J. B., Rampersad, C. J., & Pronovost, P. J. (2009). Clinical review: Checklists - translating evidence into practice. Critical Care, 13(6), 1–9. https://doi.org/10.1186/CC7792/FIGURES/4

Witte, M., & Chaparro, R. (2015). Duo Technologies Inc., Vehicle undercarriage examiner development progress in 2014.

Witte, M., Chaparro, R., & Meddah, A. (2017). Undercarriage Inspection of Railcars Using Duos Technologies VUE TM System. https://aar.com/TD-eLibrary/details.php?ID=934

Witte, M., & Lindeman, B. (2017). Undercarriage and Truck Component Inspection of Railcars Using New Vision TFDS. https://aar.com/TD-eLibrary/details.php?ID=936

Wong, T. T., & Yeh, P. Y. (2020). Reliable Accuracy Estimates from k-Fold Cross Validation. IEEE Transactions on Knowledge and Data Engineering, 32(8), 1586–1594. https://doi.org/10.1109/TKDE.2019.2912815

Wu, Z., Ming, X. G., Song, W., Zhu, B., & Xu, Z. (2012). Nuclear product design knowledge system based on FMEA method in new product development. Arabian Journal for Science and Engineering, 39(3), 2191–2203. https://doi.org/10.1007/S13369-013-0726-7/METRICS

XGBoost. (2022). GeeksforGeeks. https://www.geeksforgeeks.org/xgboost/

Xu, K., Tang, L. C., Xie, M., Ho, S. L., & Zhu, M. L. (2002). Fuzzy assessment of FMEA for engine systems. Reliability Engineering and System Safety, 75(1), 17–29. https://doi.org/10.1016/S0951-8320(01)00101-6

Yamini. (2021). Random Forest — Ensemble method. Medium. https://medium.com/geekculture/random-forest-ensemble-method-860aaf4fcd16

Yıldırım, U., Başar, E., & Uğurlu, Ö. (2019). Assessment of collisions and grounding accidents with human factors analysis and classification system (HFACS) and statistical methods. Safety Science, 119, 412–425. https://doi.org/10.1016/J.SSCI.2017.09.022

Yucesan, M., Gul, · Muhammet, & Celik, · Erkan. (2021). A holistic FMEA approach by fuzzy-based Bayesian network and best-worst method. Complex & Intelligent Systems, 7, 1547–1564. https://doi.org/10.1007/s40747-021-00279-z

Zhan, Q., Zheng, W., & Zhao, B. (2017). A hybrid human and organizational analysis method for railway accidents based on HFACS-Railway Accidents (HFACS-RAs). Safety Science, 91, 232–250. https://doi.org/10.1016/j.ssci.2016.08.017

Zhang, Z., & Liu, X. (2020). Safety risk analysis of restricted-speed train accidents in the United States. Journal of Risk Research, 23(9), 1158–1176. https://doi.org/10.1080/13669877.2019.1617336

Zheng, Z., Lu, P., & Tolliver, D. (2016). Decision tree approach to accident prediction for highway-rail grade crossings: Empirical analysis. Transportation Research Record, 2545, 115–122. https://doi.org/10.3141/2545-12

Zhou, J. L., & Lei, Y. (2018). Paths between latent and active errors: Analysis of 407 railway accidents/incidents' causes in China. Safety Science, 110, 47–58. https://doi.org/10.1016/j.ssci.2017.12.027

Zhu, R., Hu, X., Hou, J., & Li, X. (2021). Application of machine learning techniques for predicting the consequences of construction accidents in China. Process Safety and Environmental Protection, 145, 293–302. https://doi.org/10.1016/J.PSEP.2020.08.006

Zimmermann, H.-J. (2001). Fuzzy Set Theory—and Its Applications. In Fuzzy Set Theory—and Its Applications. Springer Netherlands. https://doi.org/10.1007/978-94-010-0646-0

Zúñiga, A. A., Fernandes, J. F. P., & Costa Branco, P. J. (2019). A Fuzzy-Based Failure Modes and Effects Analysis (FMEA) in Smart Grids. Advances in Intelligent Systems and Computing, 918, 507–516. https://doi.org/10.1007/978-3-030-11890-7_49

Appendices

Appendix 1. Description of features used for the analysis of HRGC accidents

No.	Feature name	Description
1	Access	Public (maintained by a road authority and designed for public use) or private crossing.
2	Regulator	Authority regulating the grade crossing, either federal or provincial.
3	Protection	Type of warning at crossing: passive (signs only), active – FLB (flashing lights and bells), or active – FLBG (flashing lights, bells, and gates).
4	Accident	The number of accidents over the last 5 years at this location. Data provided by the Transportation Safety Board (TSB).
5	Trains_Daily	Estimate of the number of freight and passenger train movements per day over given HRGC.
6	Vehicles_Daily	Estimate of the number of road vehicles per day over given HRGC.
7	Train_Max_Speed_ (mph)	Estimate of the maximum train speed over given HRGC in miles per hour.
8	Road_Max_Speed_ (km/h)	The road vehicle speed over given HRGC in kilometres per hour.
9	Lanes	Number of road vehicle lanes at this grade crossing.
10	Tracks	Number of train tracks at this grade crossing.

11	IsUrban	Indication of if this grade crossing is located in an urban (Y) area or not (N).

Appendix 2. Description of features used for analysis of the severity of casualties associated with HRGC accidents.

No.	Feature name	Description
1	Season	The season in which the accident happened.
2	OccTime	The hour of occurrence for a given accident.
3	NumberTrainsInvolved	Number of trains involved in crossing accident.
4	TotalRSInvolved	Total number of rolling stocks involved in crossing accident.
5	TrackTypeID	Type of track on which crossing accident happened (a number is given by the system).
6	TrackOwnerID	The owner of a track on which a crossing accident happened (railway/private).
7	NumTracksInvolved	Number of tracks involved in HRGC accident.
8	NumTracks	Total number of tracks involved in HRGC accident.
9	CrossingTypeID	Type of HRGC at which HRGC accident happened. (private/farm/public automated/public passive).
10	ImpactTypeID	Type of impact between train and vehicle on highway (struck vehicle/struck by vehicle).
11	CrossingLocationID	Location of crossing on which HRGC accident happened (rural/urban/private/industrial).

12	NumTrainsDaily	Number of freight and passenger train movements per day over given HRGC.
13	NumVehiclesDaily	Number of road vehicles per day over given HRGC.
14	RoadSpeed_KPH	Designated speed of highway on which HRGC is located.
15	AWDTypeID	Type of warning device installed at HRGC.
16	NumVehiclesInvolved	Total number of vehicles involved in HRGC accident.
17	DriverActionID	Number describing the driver's action in a HRGC accident.
18	NumOfOccupants	Number of occupants in the vehicle in a HRGC accident.
19	VehicleTypeID	Type of vehicle involved in HRGC accident, such as bicycle, motorcycle, van etc.
20	Train_Max_Speed	Designated speed of railroad on which HRGC is located.
21	Final_Class	Output variable that describes the severity of accident.

Appendix 3. Fuzzy rules for a fuzzy-FMEA system of TIPS

1 If Severity is Low, Occurrence is Low, and Detectability is Likely then RPN is Low
2 If Severity is Low, Occurrence is Low, and Detectability is Medium then RPN is Low
3 If Severity is Low, Occurrence is Low, and Detectability is Unlikely then RPN is Low
4 If Severity is Low, Occurrence is Medium, and Detectability is Likely then RPN is Low
5 If Severity is Low, Occurrence is Medium, and Detectability is Medium then RPN is Low
6 If Severity is Low, Occurrence is Medium, and Detectability is Unlikely then RPN is Medium

7	If Severity is Low, Occurrence is High, and Detectability is Likely then RPN is Medium
8	If Severity is Low, Occurrence is High, and Detectability is Medium then RPN is Medium
9	If Severity is Low, Occurrence is High, and Detectability is Unlikely then RPN is Medium
10	If Severity is Medium, Occurrence is Low, and Detectability is Likely then RPN is Medium
11	If Severity is Medium, Occurrence is Low, and Detectability is Medium then RPN is Medium
12	If Severity is Medium, Occurrence is Low, and Detectability is Unlikely then RPN is Medium
13	If Severity is Medium, Occurrence is Medium, and Detectability is Likely then RPN is Medium
14	If Severity is Medium, Occurrence is Medium, and Detectability is Medium then RPN is Medium
15	If Severity is Medium, Occurrence is Medium, and Detectability is Unlikely then RPN is Medium
16	If Severity is Medium, Occurrence is High, and Detectability is Likely then RPN is Medium
17	If Severity is Medium, Occurrence is High, and Detectability is Medium then RPN is High
18	If Severity is Medium, Occurrence is High, and Detectability is Unlikely then RPN is High
19	If Severity is High, Occurrence is Low, and Detectability is Likely then RPN is Medium
20	If Severity is High, Occurrence is Low, and Detectability is Medium then RPN is Medium
21	If Severity is High, Occurrence is Low, and Detectability is Unlikely then RPN is High
22	If Severity is High, Occurrence is Medium, and Detectability is Likely then RPN is Medium

23	If Severity is High, Occurrence is Medium, and Detectability is Medium then RPN is High
24	If Severity is High, Occurrence is Medium, and Detectability is Unlikely then RPN is High
25	If Severity is High, Occurrence is High, and Detectability is Likely then RPN is High
26	If Severity is High, Occurrence is High, and Detectability is Medium then RPN is High
27	If Severity is High, Occurrence is High, and Detectability is Unlikely then RPN is High

Appendix 4. Fuzzy-FMEA analysis of TIPS

No	Item	Potential Failure mode	Potential effect of failure	Severity	Potential causes of failure	Occurrence	Current design control	Detectability	Fuzzy-RPN
1	AEI tag reader	Loss of power supply to AEI reader	Failure to sense the presence of train and failure to start the TIPS	5	Power supply failure	3	Auxiliary power using a battery is available for a few hours and after that no backup supply.	2	84.5
		Malfunction of tag reader	Failure to read the RFI tag & failure to assign images to correct car ID	1	Failure of radio frequency transponders	3	Inspection frequency is once per year. Remote CCI can check the health of tag reader by logging into system.	1	53
		Track circuit failure	Failure to sense the presence of train and failure to start the TIPS	5	Track condition-shunting	3	Inspection frequency is once per year. Railway organization can check the health of track circuit by	2	84.5

							logging into system.		
		Failure of wheel sensor	Failure to read the RFI tag & assign images to correct car ID	1	Damage due to hanging foreign objects	1	Additional wheel sensors are available on site; technician needs to go on site and replace it. Remote CCI can check the health of wheel sensor by logging into system.	2	51.1
2	Camera	No clear camera images	Full view block in images	5	Banding/blurring/darkening/over-exposure in cameras	5	Remote CCI performs visual check for checking full view blockage in images.	2	104
			Partial view block in images	3	Banding/blurring/shadowing/over-exposure in cameras	5	By visual check remote CCI can detect the issue in images.	2	84.5
					Blowing snow in Maple Creek	5	Fencing is provided on north side of TIPS portal to restrict incoming snow and is performing well.	2	84.5
					Camera shutter	3	Inspection frequency is	2	63.8

					actuator malfunction		once every two months.		
		Black images from a camera	No image from cameras	5	Environmental conditions, dirt, & waterlogging	2	To avoid waterlogging, the track is elevated above the ground.	3	84.5
					Electric overloading	2	During the design phase, power requirement for camera system is calculated and sufficient power supply is allocated accordingly.	3	84.5
					Lights failure	1	Inspection frequency is once per two months	3	67.5
3	Cable	Damage to fibre cable for data transfer	Storage of images on local servers but not able to see on server.	5	Insulation damage and continuity loss for cable	2	Inspection frequency is once per year. Images cannot be accessed; remote CCI can notice a failure to connect and dispatch the technician.	2	84.5
		Damage to power cable	No image capturing as TIPS is out of power	5	Insulation damage and continuity loss for cable	3	Images would not be captured. Failure can be noticed by remote CCI.	2	84.5

4	Power suppl y	Loss of power supply	No power supply & no image of railcars	5	Power line damage due to animal attack	1	Power lines are underground, thus very unlikely.	2	67.5
					Power outage in the region due to wind or blowing snow	2	The external hard wire connection is available on-site to connect electric generator in case of power outage.	2	84.5
					Lighting strike on TIPS equipment	2	Lightning protection is provided on TIPS equipment.	2	84.5
					Power overloading from supply source	1	Two circuit breakers are available to protect the electronics from electric overloading condition.	2	67.5
		Loss of partial power supply	No images from certain camera view systems	5	Power distribution unit failure	5	A notification about any problem is sent to vendor and then vendor contacts remote CCI about problem.	2	104
5	Heate r/ blowe r	Malfunct ion of heater/ blower	Partial view block in images due to snow	3	Power failure to heater/blow er	4	Inspection frequency once every two months, but no	3	73.9

							backup for power.		
					Failure of thermostat	2	Inspection frequency is once per year.	3	63.8
			Full view block in images due to snow	5	Power failure to heater/blower	4	Inspection frequency once every two months, but no backup for power.	3	102
					Failure of thermostat	2	Inspection frequency is once per year.	3	84.5
6	Bungalow air conditioner	Malfunction of air conditioner	Bungalow temperature increase - effects on bungalow internal & instruments. Some systems can also go down.	5	Power failure to AC	2	Inspection frequency is once every two months, but no power backup	3	84.5
					Loss of refrigerant in AC	1	Two AC units in bungalow, with only one operating at a time. Inspection frequency is once every two months.	3	67.5
7	Algorithm/Software issue	Improper image stitching	Distortion in image (When a change in speed is large/small, distortion in images will be large/small)	3	Change of speed train while passing through TIPS	4	Instruction about maintaining same speed while passing through TIPS.	2	73.9

		Beena vision software breakdown (TruckView, CSCView, AHView)	Failure of some camera systems of TIPS and no image capturing using that camera system	5	Software update requirement	5	Necessary for system update. No design control.	2	104
8	Car Repair Billing (CRB) portal	CRB portal not accessible/ malfunction	Not generating BO for yard employee	1	Lost internet connectivity	1	All servers have backups, and many devices are dual threaded (using multiple providers). So whenever needed they can switch.	1	51.1
					Software update	2	Prior intimation from SAP software about the software update and outage.	1	51.1
9	Server /cloud storage	Server/cloud system breakdown	Inaccessibility of images from WISE server for inspection	1	Loss of connectivity to server/cloud	3	The company has one internal server other than WISE server only for storing images.	2	53

Appendix-5 Addressed comments from committee members.

Why are principal component analysis (PCA) and multilinear regression not used for feature selection?

Response: The PCA method is used to extract the smaller dataset from a large dataset. Also, PCA is a feature extraction technique which reduces the dataset by introducing new set of uncorrelated variables called principal components. It is true that the principal components themselves do not have a direct relationship with the original features. Therefore, the interpretation of the principal components in terms of the original features may not always be straightforward. In HRGC datasets, we are focusing on identifying the importance of features in classification problem. Hence, PCA is not used for feature selection.

The multilinear regression is used when the input features are independent of each other and dependent only on output feature. In this technique, output feature is continuous variable is predicted by defining the weights of input features. The ML models' output is classification classes which are categorical variables, not continuous variable. Thus, this method is not suitable for the feature selection from HRGC accident datasets.

The ExtraTree classifier is embedded technique based on DTs. It is efficient in handling irrelevant, redundant data, and intercorrelation of features in the dataset. For HRGC datasets, highway traffic and number of highway lanes, train traffic and number of tracks are interrelated features, which are well handled by ExtraTree classifier. Also, it is robust for with noisy data and provides a feature importance value for each feature which is helpful in selecting the relevant features for machine learning model development. Thus, ExtraTree classifier was selected to perform feature selection in HRGC datasets.

Why did you not choose normalization of dataset for ML model development?

Response: The normalization approach is used to scale the features of large dataset into a smaller range by incorporating various techniques such as mean-standard-deviation-based normalization, min-max based deviation-based normalization methods. In HRGC safety analysis, the focus was on identifying the importance of features toward HRGC accident and severity of casualty. If we normalized of the features then weightage of individual features will have diminished and correct correlation of input features to output features will have shown biased results. Also, HRGC datasets contained few categorical variables. When normalization is performed on these categorical variables, its meaningfulness will not be valuable for analysis purpose. Hence, we didn notnormalize thedataset prior toML model development.

What is daytime train movement and nighttime train movement variables mentioned on Page-no. 14?

Response: In the study of HRGC safety which was performed by Zheng et al. (2016), daytime train movement means the number of trains through HRGC during daytime and nighttime train movement means the number of trains through HRGC during nighttime. The study used DAYTHRU and NGHTTHRU as two variables for daytime train movement and nighttime train movement, respectively.

Why is triangular member function (MF) used for conducting fuzzy-FMEA analysis of TIPS system?

Response: The comparison of various membership function was performed in a study by Princy & Dhenakaran (2016) reported that the triangular and trapezoidal MFs than Gaussian MF. However, when triangular and trapezoidal MFs were analyzed, it was observed that the triangular membership function consumed less memory usage. Also, the triangular MF exhibits the normal distribution characteristics like Gaussian membership function to some extent, such as highest membership function at one point and symmetry on both sides. Hence, to maintain the similar distribution, triangular membership function was selected for fuzzy-FMEA analysis of TIPS system.

How did you choose 80:20 split ratio for train-test data split and how is K-fold cross validation is used for HRGC datasets?

Response: The different train-test split ratio for splitting dataset on machine learning model may affect the accuracy value of ML model. Thus, K-fold cross validation is performed to evaluate the robustness of model on the entire dataset. The K-fold cross validation keeps K^{th} part of dataset for validation and uses K-1 part of dataset for training the ML model. This process is repeated for K times and model is trained on entire dataset. Finally, the model performance is aggregated for evaluation of ML model. Using K-fold cross-validation aids in achieving a more robust evaluation by mitigating the influence of the specific data partitioning on the performance metrics, thus enhancing the robustness of the assessment. Hence, started by selecting 80:20 split ratio followed by K-fold (10-fold) cross validation which helped in aggregating the ML model results.

How can future analysis be done based on clustering results for improving safety of HRGC?

Response: Further analysis of HRGC safety can focus on identifying the safety critical HRGCs within the clusters that have been identified. This can be achieved by examining various features associated with HRGC locations, as well as factors related to both the highway and railroad and incorporating experts' judgement. By assessing the criticality of each HRGC of cluster, recommendations and solutions can be developed. These recommendations should consider the feasibility of stakeholders' concerns, budget constraints, and the potential positive impact on public safety, environmental considerations, and HRGC safety.