Received May 24, 2020, accepted June 8, 2020, date of publication June 15, 2020, date of current version June 30, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3002416

Artificial Intelligence Enabled Road Vehicle-Train Collision Risk Assessment Framework for Unmanned Railway Level Crossings

VIVEK SINGHAL[1], S. S. JAIN[2], DIVYA ANAND[3], AMAN SINGH[3], SAHIL VERMA[3], (Member, IEEE), KAVITA[3], (Member, IEEE), JOEL J. P. C. RODRIGUES[4,5], (Fellow, IEEE), NOOR ZAMAN JHANJHI[6], (Senior Member, IEEE), UTTAM GHOSH[7], (Senior Member, IEEE), OHYUN JO[8], (Member, IEEE), AND CELESTINE IWENDI[9], (Senior Member, IEEE)

[1]Department of Information Technology, JSS Academy of Technical Education, Noida 201301, India
[2]Department of Civil Engineering, Indian Institute of Technology Roorkee, Roorkee 247667, India *(Retired)*
[3]Department of Computer Science and Engineering, Lovely Professional University, Phagwara 144401, India
[4]Federal University of Piauí (UFPI), Teresina 64049-550, Brazil
[5]Instituto de Telecomunicações, 1049-001 Lisboa, Portugal
[6]School of Computer Science and Engineering, Taylor's University, Subang Jaya 47500, Malaysia
[7]School of Computer Science and Engineering, Vanderbilt University, Nashville, TN 37235, USA
[8]Department of Computer Science, College of Electrical and Computer Engineering, Chungbuk National University, Cheongju 28644, South Korea
[9]Department of Electronics, BCC of Central South University of Forestry and Technology, Changsha 410004, China

Corresponding authors: Sahil Verma (sahilverma@ieee.org) and Ohyun Jo (ohyunjo@chungbuk.ac.kr)

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. NRF-2018R1C1B5045013); by FCT/MCTES through national funds and when applicable co-funded EU funds under the Project UIDB/EEA/50008/2020; and by National Council for Scientific and Technological Development (CNPq) via Grant No. 309335/2017-5.

ABSTRACT The study focuses on the artificial intelligence empowered road vehicle- train collision risk prediction assessment, which may lead to the development of a road vehicle-train collision avoidance system for unmanned railway level crossings. The study delimits itself around the road vehicle-train collisions at unmanned railway level crossings on single line rail-road sections. The first objective of the study revolves around the rail-road collision risk evaluation by the development of road vehicle-train collision frequency and severity prediction model using Poisson and Gamma-log regression techniques respectively. Another study objective is the collision modification factor implementation on predicted risk factors, to reduce the road vehicle-train collision risk at the crossings. The collision risk has been predicted to be 3.52 times higher and 77% lower in one direction while in other directions it is 2.95 times higher and 80% lower than average risk at all unmanned railway level crossings. With collision modification factor application on higher risk contributing factors i.e. 'crossing angle' and 'train visibility, it predicts to reduce the road vehicle-train collision risk to 85% approximately.

INDEX TERMS Artificial intelligence, unmanned railway level Crossings, road vehicle-train collisions, frequency, severity, regression, collision modification factor (CMF).

I. INTRODUCTION

A railway level crossing is a place where rail and road cross each other at the same level. The approaching train has a higher priority to pass over the unmanned railway level crossings in comparison to the road vehicles and pedestrians approaching the railway crossings. However, there is no control over road vehicle-train collisions at unmanned railway level crossings. The level crossing accidents per million train km has been 4 times higher than the level crossing accidents per million train km statistics of France, while it is 2 times higher in comparison to the level crossing accidents per million train km in Japan [1]. The Indian accident scenario goes to the worst possible statistics with deaths per level crossing being 14 times and 7.58 times higher in comparison to deaths per level crossing in France and Japan

The associate editor coordinating the review of this manuscript and approving it for publication was Amr Tolba.

respectively [1]. The railway level crossings contribute 43% (50 out of 117) of all consequential train accidents and 67% fatalities (101out of 149) of total fatalities. The railway level crossings are of two types viz. manned railway level crossings and unmanned railway level crossings. Indian Railways network [2] had 30,348 level crossings (as on 01.04.2014) out of which, 18,725 (62%) were manned railway level crossings and 11,563 (38%) were unmanned railway level crossings [3]. According to Indian Railways, out of 11563 unmanned railway level crossings, 730 unmanned railway level crossings were targeted to be eliminated in the year 2014 [4].

Therefore, the study focuses on AI-empowered road vehicle- train collision risk assessment, which may further help in the development of a cost-effective and reliable road vehicle-train collision avoidance system for the protection of unprotected railway level crossings. The motivation of the study comes from the fact that to partially improve road user safety, it is necessary to assess the road-vehicle train collision risk factors at unmanned railway level crossings. The continuous road vehicle-train collisions at unmanned railway level crossings is a major problem faced in the present scenario especially in villages and small cities. Therefore, to improve driver safety, it is necessary to assess the high-risk factors contributing to the road-vehicle train collisions at unmanned railway level crossings.

The primary objective of the research is to develop an AI-based road vehicle-train collision risk prediction model and its countermeasure implementation for the avoidance of accidents at unmanned railway level crossings. To achieve this, the study includes the following sub-objectives-The the first objective of the study lies in the development of a rail-road collision risk assessment model on collision prone unmanned railway level crossings. Therefore, a risk prediction system is to be modeled by developing a road vehicle-train collision frequency and severity prediction model using Poisson regression and Gamma-log regression techniques respectively. Another objective is to apply a collision reduction countermeasure on high collision risk factors to reduce the road vehicle-train collisions at the crossings.

The main contributions of the study areas-

- The train visibility and crossing angle have been found to most significant parameters for road vehicle collision risk prediction.
- The road-vehicle train collision risk has been predicted to be 3.52 times higher on C-140 and the lowest risk (C-87) has been observed to be 77% (approx.) lower than average risk at all unmanned railway level crossings in direction 1. While, in direction 2, C-136 is 2.95 times higher and C-87 has 80% (approx.) lower predicted risk than average risk at all unmanned railway level crossings.
- When Collision Modification Factor (CMF) is being implemented on train visibility, crossing angle, Average Daily Traffic (ADT) of minibus/bus, scooter/motorcycle, rickshaw and number of trains, train visibility, PCR, road width, and crossing angle, the road vehicle-train collision risk predicts to decrease to 85% (approx.).

The paper has been organized into five sections. Section I discusses the focus, motivation, problem, objectives, definitions, and main contributions of the study. Section II reviews the studies done in the past related to the work. Section III talks about research methodology, it is being organized into three sections- data collection and modeling and validation. Section IV presents the results and discussion of the proposed work. The last section discusses the conclusions and further research opportunities for the proposed study.

II. RELATED WORK

In this section, the study discusses the existing rail/road collision risk prediction techniques developed over the world.

Gitelman *et al.* [5] evaluated the rail/road collision risk prediction modeling for Israeli 186 railway level crossings. The modeling was being done using the Israeli accident limited data of six years. The accident data was modeled with the help of crossing types defined by various crossing characteristics. The collision prediction study resulted in estimation for the need for rail/road collisions countermeasure i.e. grade separation to avoid rail/road collisions. Anderson *et al.* [6] estimated the risk of road vehicles approaching the railroad crossing. Therefore, the probability of the derailment of the road vehicle from the road due to train approaching information was calculated by Eqn. (1)-

$$\Pr(der) = \sum R_i m_i \tag{1}$$

where R_i = derailment rate per mile for class 'i' track and m_i = mileage traversed on the class 'i' track.

Lee *et al.* [7] developed a road vehicle-train collision frequency model using one hundred collision prone railway grade crossings of Korea. The regression techniques were used to model the accident frequency using Zero-inflated modeling techniques. The regression was done for two states– firstly, the Poisson accident state and the other one is the zero-accident state. In Poisson accident state, the grade crossing characteristics viz. building indicator (1 if the presence of buildings,0 otherwise), guardrail indicator (1 if the presence of guardrails, 0 otherwise), hump indicator (1 if the presence of humps, 0 otherwise), number of lanes, stop sign indicator (1 if the presence of stop signs, 0 otherwise) and grade crossing characteristics viz. angle (degrees), control device indicator (1 if the presence of control devices, 0 otherwise), management indicator (1 if the KNR manages, 0 otherwise), number of tracks right clearing sight distance (in meters), right grade indicator (1 if the presence of right grades, 0 otherwise) and warning time (in a sec) were found to be most statistically significant variables for accident frequency prediction. In accident state, the Annual Average Daily Traffic (AADT), building indicator (1 if the presence of buildings, 0 otherwise) was found to be the most significant variable. The marginal effects of these factors were computed to indicate the effectiveness of potential countermeasures. The marginal effect analysis of all significant variables in the Poisson accident state suggested that less sight distance, incorrect grade indicator, right grades, and urgent stop of vehicles on tracks, larger warning time tended to increase the accident frequency at railroad crossings. The zero-accident state suggested that a rise in AADT, wide lanes also predicted to rise with accident frequency increase at railroad crossings. In [8], a negative binomial regression-based collision prediction model was developed for American railway level crossings. The significant factors viz. drunk driving and emergency medical response improvement, approximately 40% collisions at unmanned railway level crossings were predicted to decrease. The traffic control measures improvement helped in decreasing the collisions to 20%. Oh, *et al.* [9] developed an accident frequency model using the gamma probability model for the United States railway level crossings. The railway level crossing safety elements were obtained and evaluated using Korean data. The study indicated that with an increase in total traffic volume and average daily train volumes, there was a rise in railroad accidents. The railroad accidents tended to increase when railroad crossings were near to commercial areas. It also expressed the distance of the train detector setup, which detected the obstacles [10] i.e. if decreased, the probability of accidents tended to increase. The time duration of warning signals and gates activation, when increased, predicted to increase the accidents. Lee *et al.* [11] developed a railway level crossing risk models to analyze the safety aspect of Taiwan railway level crossings using Poisson and negative binomial regression. The study discussed the risk in terms of a product of accident likelihood (number of accidents per period) and the accident impact (fatalities per accident). The parameters considered for risk assessment were road characteristics, railway characteristics, and the control devices at railway level crossings. The results indicated that Poisson regression was the best estimator of accident likelihood; and negative binomial regression was the best technique for accident impact evaluation. Federal Highway Administration [12] presented the unmanned railway level crossing accident frequency prediction models such as the Peabody Dimmick Formula, the New Hampshire Index, the National Cooperative Highway Research Program, Hazard Index (HI), and the US DOT's three-stage Crash Prediction Formula.

McCollister *et al.* [13] developed a model to predict road vehicle-train collision frequency, injuries, and fatalities for the U.S.A. railway level crossings. The independent variables used for the logistic regression were viz. maximum typical train speed, trains/day, trucks percentage, traffic per lanes, stop signs, other signs, crossbucks, activated protection, wigwags, flashing lights, angle of crossing (0 degrees to 59 degrees), track down street, area residential/commercial/industrial and accident history. The results indicated that accident history and traffic congestion were found to be the most significant variables for crash frequency and severity prediction. The model also calculated the cost per life saved with an assumption of a discount rate of 6.1 percent and an inflation rate of 2.2 percent. Therefore, an annual cost of $7378 was required to enhance with flashing lights. Again, to upgrade from flashing lights an annual cost of $10 382 was required.

Hu *et al.* [14] developed a road vehicle- train collision frequency model using the NB regression model and road vehicle- train collision severity model using the logit regression. The road vehicle- train collision frequency modeling was modeled using the daily trains, AADT while road vehicle- train collision severity model was developed using the train speed, daily trains, and AADT/1000. The countermeasure evaluation was also done using the Poisson regression model i.e. by modifying track number, transforming crossing type, and regulating traffic exposure for road vehicle- train collision reduction. Hu *et al.* [15] developed a collision severity model using zero-inflated Poisson regression for 592 Taiwan railway level crossings. The number of trains, annually-averaged daily traffic, crossing angle, and the presence of guidance signs was significantly associated with the collision severity model. The traffic exposure, crossing angle, and traffic signage were found to be significant effects on the accident severity model development. Hao *et al.* [16] developed a railroad collision severity model for highway-rail grade crossings using an ordered probit model. The factors viz. crash occurred during the peak hour, weather, visibility (meters), vehicle type, vehicle speed in m/sec, AADT in veh/day, train speed in km/hr, driver's age, gender (male/female), area type and highway pavement were found to be most significant for driver injury severity modeling. The marginal effect analysis was done to study the effects of each significant factor for driver injury modeling. Hao *et al.* [17] performed the rail/road severity modeling for railway level crossing using the logit model under different weather conditions. To perform this modeling, the collision data (2002-2011) of highway-rail grade crossing was used as a dependent variable. The results indicated that the driver's injury severity was not a constant factor. It was found that the factors viz. road vehicle speed, train speed, age of the driver, gender, area type, external lighting, road condition, traffic volume, and time of day significantly affected the collisions considerably under weather conditions. Therefore, the higher the road vehicle or train speed, the greater the crashes, and therefore, the higher the level of collision severity. The severity predicted to rise with age. The fatality roses by 51% under fog condition. Again, the fatality increased by 45% under rain condition, also rose by 39% under snow condition. The injury fatalities increased again by 28% under cloudy conditions, and by 16% under clear weather conditions. Hu *et al.* [18] developed a collision severity prediction model using 27 independent variables from 35 parameters using logit or probit models. The results indicated that the developed model was the best in collision frequency prediction. Zheng *et al.* [19] modeled the traffic risk of the unmanned railway level crossings using the Petri nets. The risk management parameters of the six countries viz. china, Slovakia, Poland, Morocco, Bulgaria, and Finland were calibrated. Thereafter, the model validation was done by the accident data (2002 and 2006) for all six countries. The model predicted the accident rates for the year 2010 and also found it to be almost 95% effective for modeling the risk at unmanned railway level crossings.

Therefore, studies revealed that there is a very small degree of unmanned railway level crossings data collection, implementation, and analysis of road vehicle-train collision frequency and severity prediction models for unmanned railway level crossings in India.

III. MATERIALS AND METHODS

A. DATA COLLECTION

As evident from the previous studies, the road vehicle-train collisions at unmanned railway level crossings are generally caused by unawareness of road drivers about an increased number of trains approaching the unmanned railway level crossings, avoidance of railroad safety rules on approach by road vehicles on unmanned railway level crossings, wrong interpretation of approaching train speed [20] on unmanned railway level crossings by road vehicles, improper unmanned railway level crossings approach road geometrics, unmanned railway level crossings geometric deficiencies, and also by environmental defects.

The study is being conducted on an Indian railway line section of Shahdra-Shamli-Tapri (DSA-SMQL-TPZ), which connects Shahdra (inside Indian city, Delhi) through Shamli (a city in India) to Tapri (a town near Saharanpur City in India). The railway line is about 165 km in length and it has 145 railway level crossings and 71 of them are unmanned railway level crossings. The railway line connects the major cities of Uttar Pradesh and Delhi. The unmanned railway level crossings on this railway route are situated mostly near rural areas i.e. (approximately 95%).

The railway route operation and maintenance are done by Northern Railways (NR), a division of Indian Railways (IR). The study has been conducted on 19 road vehicle-train collision prone unmanned railway level crossings situated on the DSA-SMQL-TPZ railway route with railway line chainage between 0 km to 165 km. The study route map is shown in Fig. 1.

According to Safety Information Management System (SIMS), the maximum design and booked speed on the DSA-SMQL-TPZ section is 75 km/hr and in foggy conditions, the maximum permissible speed of the train is 48 km/hr. The study area details with directions are given in Table 1. The length of the road crossing in Table 1 has been calculated from intersection in one side to another one.

The data and its collection method are given in Table 2.

The road vehicle-train collision frequency at the DSA-SMQL-TPZ railway route is given in Fig. 2. The road vehicle-train collision frequency is observed to be highest i.e. 0.4 in case of unmanned railway level crossings 14-C, 16-C, 34-C, 50-C, 72-C,122-C, and 133-C, while other remaining unmanned railway level crossings road vehicle-train collision frequency is approximately 50% lower than these crossings.

The road vehicle- train collision severity level [21] is decided according to what type of problem happens to a road vehicle-train collision occurrence victim at unmanned railway level crossings. The road vehicle-train collision severity is a combination of the total number of persons killed, having a grievous injury, and simple injury. The road vehicle severity levels are shown in Table 3. The description of each type of severity is given as in Table 4.

B. DATA DISTRIBUTION TEST

Data distribution testing is the distribution of the response variable ''road vehicle-train collision frequency'' of the road vehicle-train collision data at unmanned railway level crossings as shown in Table 5. The normality test using a Kolmogorov-Smirnov test has been shown in Table 6.

In this study, the observation of the road vehicle-train collision frequency and severity is based on the collisions that occurred for the period (2009-2013). Therefore, it based on the characteristics and data distribution modeling calibration with the Kolmogorov-Smirnov test. The collision frequency and severity possibility are very small, which means that any vehicles passing the railroad crossings have a very small possibility to get involved in collisions. The average collision frequency is 1.43 and severity is found to be 2.21. Therefore, the road vehicle-train collision frequencies are about 1-2 times at one point. The Kolmogorov Smirnov test of road vehicle-train collision frequency shows the value of 0.397 with a p-value of 0.00. Further, the road vehicle-train collision severity is on average 2 -3 times in a point. The road vehicle-train collision severity Kolmogorov Smirnov test has a value of 0.319 with a p-value of 0.00.

Therefore, it may be concluded that the data on road vehicle-train collisions is followed by the Poisson and Gamma distribution, which is in turn a Generalized Linear Model (GLM) [22].

IV. THEORY AND CALCULATION

The theoretical models for AI-empowered road vehicle-train collision frequency and severity prediction models have been developed in the study. The prediction has been done for the selection of the better countermeasure for avoiding the road vehicle- train collisions at unmanned railway level crossings [23], [24]. The variables with homogenous characteristics viz. approach road gradient, number of lanes, track gradient, social awareness, road signboard presence, and number of tracks have not been included in the analysis [25].

The modeling which represents the correlation of collisions at railway crossings with 27 explanatory variables is analyzed with Poisson regression analysis. The regression techniques for prediction of collision frequency used are Poisson-identity, Poisson-log, and Poisson-power (2nd degree) regression techniques. Again, the AI-enabled road vehicle- train collision severity prediction modeling is done by using the gamma-log technique. The selected variable consists of input and target variables. The target output variable i.e. road vehicle- train collision frequency and road vehicle-train collision severity at unmanned railroad crossing has been determined by the 27 input variables

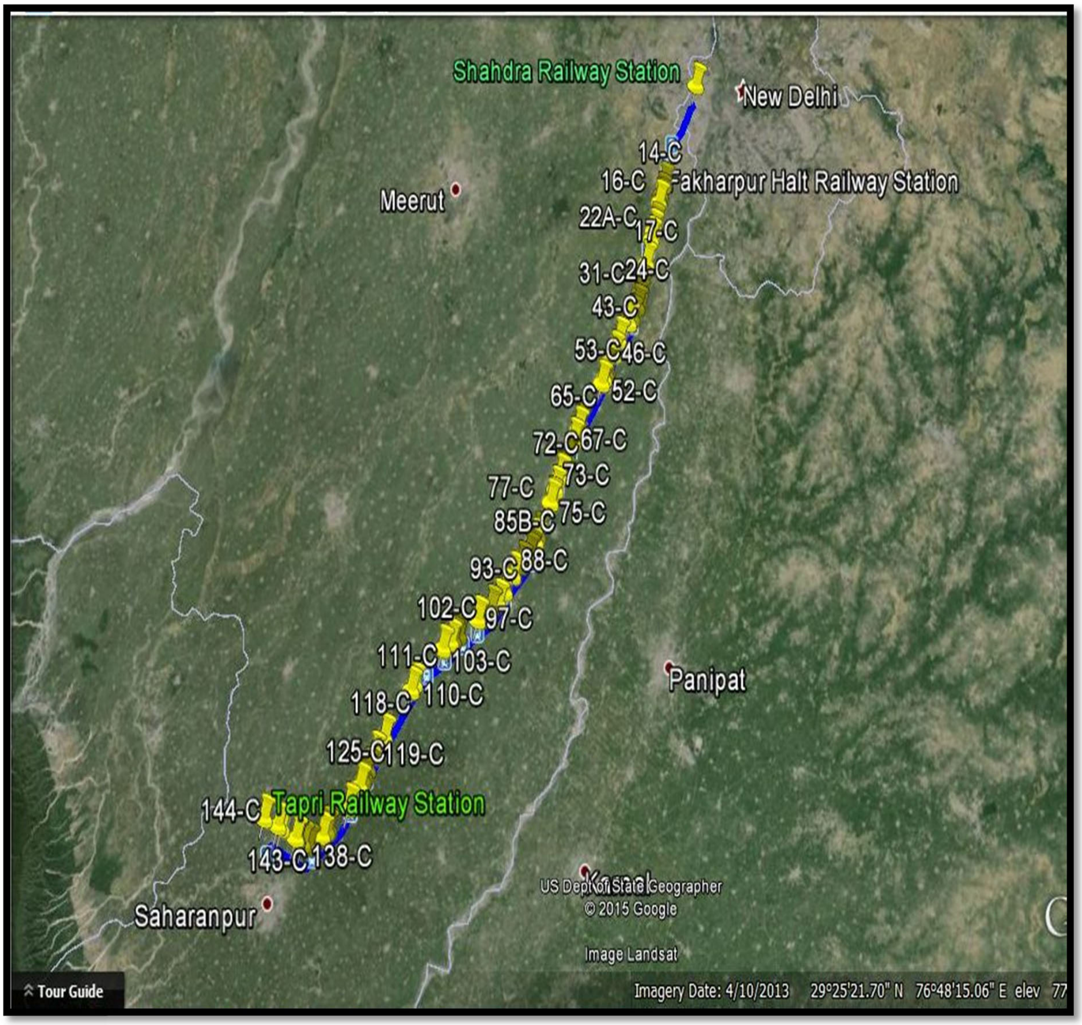

FIGURE 1. **Study route map of DSA-SMQL-TPZ (Google Earth Imagery).**

with 167 data samples namely Average Daily Traffic (ADT) of car/jeep/van, minibus/bus, scooter/motorcycle, mini-truck/truck, tractor/trailer, auto-rickshaw, rickshaw and pedestrian, train speed in m/sec, number of trains, train visibility in meters, Approach Road Gradient (ARG), Pavement condition rating (PCR), number of lanes, road width in meters, number of tracks, crossing angle in degrees, track gradient (%), social awareness, driving style (nonaggressive/ aggressive), licensed (yes/no), driver impairment (yes/no), literate (yes/no), road vehicle speed in m/sec, road signboard (presence/absence) and number of tracks. The explanatory and independent variables for road vehicle-train collision frequency and severity prediction modeling are shown in Table 7.

A. SYSTEM MODEL

1) ROAD VEHICLE-TRAIN COLLISION FREQUENCY MODELING

The covariates have been modeled using three Poisson regression techniques. The Wald Chi-square test has been conducted in each combination. The p-value statistics were tested for significance i.e. p should be less than 0.05. 2 out of 28 independent variables viz. train visibility (meters) and crossing angle (degrees) were found to be significant. The regression coefficients for road vehicle- train collision frequency prediction using Poisson-identity, Poisson-log, and Poisson-power (2^{nd} degree). The Poisson-identity, Poisson-log, and Poisson power (2^{nd} degree) models are shown in Eqns. (2) to (4).

Model A:

$$y_{\text{Poisson-Identity}} = -0.005 * \text{Train Visibility} + 0.007 * \text{Crossing Angle} + 7.755 \quad (2)$$

Model B:

$$y_{\text{Poisson-Log}} = \exp(-0.003 * \text{Train Visibility} + 0.005 * \text{Crossing Angle} + 4.512) \quad (3)$$

Model C:

$$y_{\text{Poisson-Power(2)}} = (-0.014 * \text{Train Visibility} + 0.019 * \text{Crossing Angle} + 20.933)^2 \quad (4)$$

TABLE 1. Details of selected rail/road collision prone unmanned railway level crossings.

S. No.	Unmanned Railway Level Crossing	Road passing over unmanned railway level crossing			
	Number	Block section	Direction1 (UP)	Direction 2 (DN)	Length of road crossing the unmanned railway level crossing (in km)
1	14-C	Noli Delhi-Tapri (NO-KEX)	Gotra/Mandula to Fakharpur	Fakharpur to Gotra/Mandula	3.633
2.	16-C	Noli Delhi-Tapri (NO-KEX)	Khekra to Fakharpur	Fakharpur to Khekra	1.823
3.	17-C	Noli Delhi-Tapri (NO-KEX)	Khekra to Fakharpur	Basi/Khekra to Sunhera	1.823
4.	21-C	Khekra-Baghpat (KEX-BPM)	Sunhera to Basi/Khekra	Basi/Khekra to Sunhera	3.541
5.	34-C	Baraut- Baghpat (BTU-BPM)	Saroorpur Kalan to Gaadhi	Gaadhi to Saroorpur Kalan	4.293
6.	35-C	Baraut- Baghpat (BTU-BPM)	Saroorpur Kalan to Sujra	Sujra to Saroorpur Kalan	3.222
7.	43-C	Baraut- Baghpat (BTU-BPM)	Irdispur to Badka	Irdispur to Badka	1.669
8.	50-C	Baraut-Quasimpur Kheri (BTU-KPKI)	Baoli to Latifpur to Sabha Kheri	Sabha Kheri to Baoli to Latifpur	1.432
9.	67-C	Quasimpur Kheri – Baraut (KPKI-BTU)	Ramala to Budhpur	Budhpur to Ramala	5.356
10.	72-C	Quasimpur Kheri-Kandhla (KPKI-KQL)	SH-57 to Ailum	Ailum to SH-57	0.557
11.	82-C	Kandhla-Shamli (KQL-SMQL)	PanjaKhara to Jasala	Jasala to PanjaKhara	1.135
12.	87-C	Kandhla-Shamli (KQL-SMQL)	Lilion to Balwa	Balwa to Lilion	1.710
13	93-C	Shamli-Heend (SMQL-HID)	Gohrani to Karodi	Karodi to Gohrani	2.7772
14.	103-C	Heend-ThanaBhawan (HID-THBN)	Raseedgarh to Hararfatehpur	Hararfatehpur to Raseedgarh	2.956
15.	110-C	Thanabhwan-Nanauta (THBN-NNX)	Ambeta YakubPur to Jalabad	Jalabad to Ambeta YakubPur	3.448
16.	122-C	Rampur Maniharan-Nanuta (RPMN-NNX)	Tipra to Sambhalkheri	Sambhalkheri to Tipra	2.624
17.	133-C	Rampur maniharan-Manani (RPMN-MNZ)	Jhandera to Nalhera	Nalhera to Jhandera	3.676
18.	136-C	Manani-Tapri (MNZ-TPZ)	Chunneti to NainKhera	NainKhera to Chunneti	2.085
19.	140-C	Manani-Tapri (MNZ-TPZ)	Fatehpur to Mavikhurd	Mavikhurd to Fatehpur	1.023

TABLE 2. Data collection method.

S. No.	Data collection method	Data collected
1.	Visual examination	Numbers of tracks Numbers of lanes Numbers of trains Road sign board presence/absence Weather, obstruction, and construction
2.	Speed radar gun	Train speed (spot speed) Speed of road vehicles
3.	SIMS railway official website	Track gradient Approach road gradient (ARG)
	Tally method	Road traffic volume (both directions of selected unmanned railway level crossings for seven days)
4.	Measuring Tape	Road width
5.	Other methods of data collection	Road type
6.	Spatial images from Google Earth	Crossing type (Y or T-type)
7.	Road Driver survey	Social awareness Driving style License Impairment Literacy
8.	Road-vehicle collision data	Traffic Inspector (TI) office of Shamli railway station

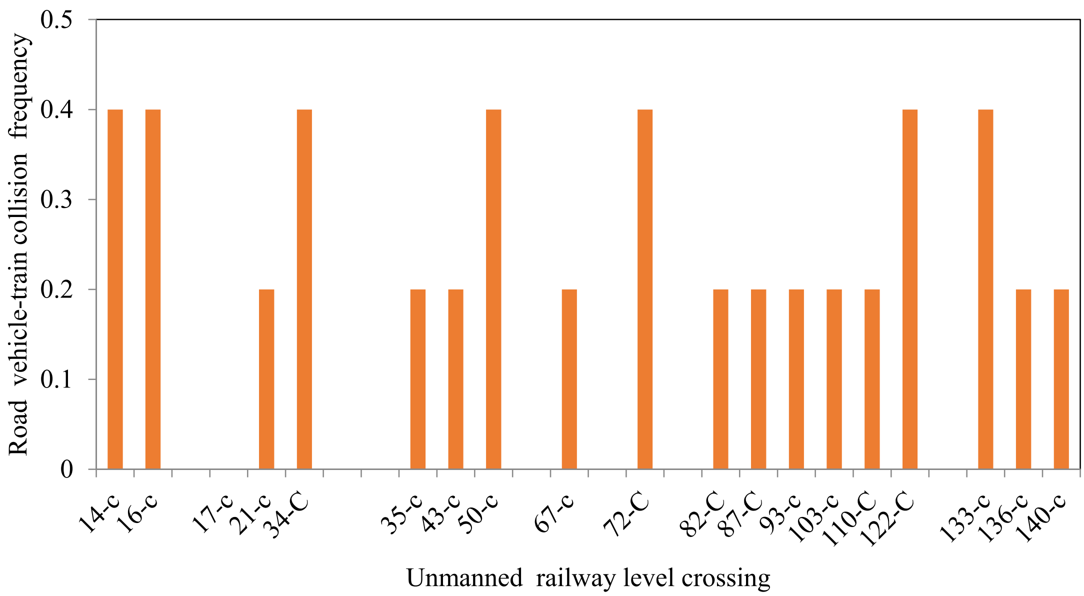

FIGURE 2. Road vehicle-train collision frequency at unmanned railway level crossing.

$y_{Poisson-identity}$ = Road vehicle-train Poisson-identity collision frequency Poisson prediction output variable

$y_{Poisson-log}$ = Road vehicle-train Poisson collision frequency prediction output variable Poisson prediction output variable

$y_{Poisson-power(2)}$ = Road vehicle-train Poisson-power (2^{nd} degree) collision frequency Poisson prediction output variable.

2) AI-ENABLED ROAD VEHICLE- TRAIN COLLISION SEVERITY MODELING

The gamma-log regression was conducted again on 27 independent variables, 9 out of 28 independent variables viz. ADT (Mini Bus/Bus), ADT (Scooter/Motorcycle), ADT (Rickshaw), train speed in m/sec, number of trains, train visibility in meters, PCR, road width in meters and crossing angle in degrees are found to be significant and equation of road vehicle- train collision severity prediction model is shown in Eqn. (5)

$$\begin{aligned} y_{gm} = \exp(&4.725 - 0.005 * \text{ADT (MiniBus/Bus)} + 0.001 \\ &* \text{ADT (Scooter/Motorcycle)} - 0.006 * \text{ADT (Rickshaw)} \\ &+ 0.074 * \text{Train Speed} - 0.219 * \text{Number of Trains} - 0.003 \\ &* \text{Train Visibility} + 0.065 * \text{PCR} - 0.33 * \text{Road Width} \\ &+ 0.004 * \text{Crossing Angle}) \end{aligned} \tag{5}$$

TABLE 3. Road vehicle- train severity.

Unmanned railway level crossing	Injuries						Road vehicle-train collision severity (during 5 years)
	Killed (32%)		Grievous (24%)		Simple (16%)		
14-C	1	8%	0	0%	3	19%	4
16-C	0	0%	0	0%	0	0%	0
17-C	1	0%	0	0%	2	0%	3
21-C	0	8%	0	0%	0	13%	0
	0	0%	0	0%	0	0%	0
34-C	2	0%	0	0%	5	0%	7
35-C	2	17%	0	0%	5	31%	7
43-C	0	17%	0	0%	1	31%	1
50-C	0	0%	0	0%	0	6%	0
	3	0%	2	0%	0	0%	5
67-C	0	25%	0	22%	0	0%	0
	0	0%	0	0%	0	0%	0
72-C	1	0%	0	0%	0	0%	1
	0	8%	0	0%	0	0%	0
82-C	1	0%	0	0%	0	0%	1
87-C	1	8%	0	0%	0	0%	1
93-C	0	8%	0	0%	0	0%	0
103-C	0	0%	0	0%	0	0%	0
110-C	0	0%	5	0%	0	0%	5
122-C	0	0%	2	56%	0	0%	2
133-C	0	0%	0	22%	0	0%	0
136-C	0	0%	0	0%	0	0%	0
140-C	0	0%	0	0	0	0	0

TABLE 4. Road vehicle- train collision severity statistics.

S. No.	Road-vehicle collision severity	Description
1.	Simple injury	An injury which is no threat to life
2.	Grievous injury	An injury which is a threat to life
3.	Killed	Death of the road drivers

where, y_{gm} = Road vehicle-train gamma-model collision severity prediction output variable.

B. VALIDATION

1) VALIDATION OF AI-EMPOWERED ROAD VEHICLE- TRAIN COLLISION FREQUENCY PREDICTION MODELS

The validation is being performed on 5 unmanned railway level crossings viz. 110-C, 122-C, 133-C, 136-C, and 140-C with 48 samples. The R^2 calculated for Poisson–identity, Poisson-log, and Poisson-power (2^{nd} degree) road vehicle-train collision frequency prediction models are- 0.531, 0.719, and 0.693 respectively, which is nearer to the significance level of 1 and thereby proves the model to be significant. Further, validation of the model has been performed using the goodness of fit statistics [26] on Poisson-identity, Poisson-log, and Poisson-power (2^{nd} degree) models as shown in Table 8 and 9

1. The deviance and scaled deviance of the Poisson-log model shows that road vehicle–train collision frequency prediction is the lowest of all three Poisson models. Therefore, the Poisson log road vehicle–train collision frequency prediction model is the most effective model for road vehicle-vehicle collision frequency prediction.
2. The Pearson Chi-Square test and scaled Pearson Chi-Square test again suggest that it is lowest in the case of the Poisson-log road vehicle–train collision frequency prediction model in comparison to other Poisson models. Therefore, it results in the best model for road vehicle-vehicle collision frequency prediction.
3. The log-likelihood value of the Poisson-log road vehicle–train collision frequency prediction model is the greatest in comparison to other Poisson models. Therefore, the Poisson-log model for the road

TABLE 5. Data distribution test.

		Road vehicle-train collision frequency (2009-13)		Road vehicle-train collision severity (2009-13)	
		Statistic	Std. error	Statistic	Std. error
Mean		1.43	.048	2.21	.205
95% Confidence Interval for Mean	Lower Bound	1.33		1.81	
	Upper Bound	1.52		2.62	
5% Trimmed Mean		1.37		2.02	
Median		1.00		1.00	
Variance		0.390		7.068	
Std. Deviation		0.625		2.658	
Minimum		1		0	
Maximum		3		8	
Range		2		8	
Interquartile Range		1		4	
Skewness		1.170	0.187	1.044	0.187
Kurtosis		0.288	0.373	-0.304	0.373

TABLE 6. Normality test.

	Kolmogorov-Smirnov		
	Statistic	df	p-value
Road vehicle-train collision frequency (2009-13)	0.397	168	<<0.05
Road vehicle-train collision severity (2009-13)	0.319	168	<<0.05

vehicle-vehicle collision frequency prediction is most effective of all Poisson models.

4. The AIC, AICC, BIC, and CAIC of the Poisson-log road vehicle–train collision frequency prediction model is again the lowest of all other Poisson models. This outputs the Poisson log road vehicle-train collision frequency model to be the best model in comparison to other Poisson models.

Therefore, the R^2 and goodness of fit statistics viz Deviance, scaled Deviance, Pearson Chi-Square [27], Scaled Pearson Chi-Square, Log-Likelihood, Akaike's Information Criterion (AIC) [28], [29], Finite Sample Corrected AIC (AICC) *[30],* Bayesian Information Criterion (BIC), Consistent AIC (CAIC) is being calculated indicated the- Poisson-log model to be most significant for road vehicle-train collision frequency prediction.

2) VALIDATION OF AI-BASED ROAD VEHICLE-TRAIN COLLISION SEVERITY MODELS

The actual road vehicle- train collision frequency has been fitted with road vehicle- train collision severity predicted and R^2 is found to be 0.739 which is close to 1 as shown in Fig. 3, which is again nearer to the significance level of 1 and thereby proves the model to be significant.

The goodness of fit for the gamma-log model road vehicle- train collision severity prediction model is shown in Table 10.

V. RESULTS AND DISCUSSIONS

A. RANK ANALYSIS

The comparison of the rank based on AI-empowered road vehicle-train collision frequency and road vehicle-train collision rate is given in Table 11. There was no change in unmanned railway level crossings viz. 17-C, 34-C, 72-C, 93-C, 103-C, and 136-C. Other, remaining road vehicle-train collision unmanned railway level crossings differed in ranking status because ranking method based on road vehicle-train collision rate is dependent on ADT (veh/hr) and these road vehicle-train collision unmanned railway level crossings ADT. The rank status based on road vehicle-train collision rate increases in comparison to rank based on road vehicle-train collision frequency in case of 17-C, 34-C, 35-C, 50-C, 67-C, 72-C, 93-C, 103-C, 110-C, 122-C, 133-C, 136-C, and 140-C road vehicle-train collision unmanned railway level crossings, while it decreases in case of road vehicle-train collision unmanned railway level crossings viz. 14-C, 16-C, 21-C,43-C, 82-C, and 87-C. In Table 11, the negative sign indicates the decrease of rank based on road vehicle-train collision rate compared to rank based on road vehicle-train collision frequency, while positive sign indicates the

TABLE 7. Road vehicle-train risk prediction modeling variables.

		Minimum	Maximum	Mean	Std. dev.
Dependent variable	Road vehicle-train collision (2009-13)	1	3	0.625	0.625
covariate(s)	ADT (Car/Jeep/Van)	46	461	114.958	114.958
	ADT (Minibus/Bus)	10	98	18.986	18.986
	ADT (Scooter/Motorcycle)	185	951	204.632	204.632
	ADT (Minitruck/Truck)	7	43	10.776	10.776
	ADT (Tractor/Trailer)	126	471	100.213	100.213
	ADT (Auto Rickshaw)	2	119	21.110	21.110
	ADT (Rickshaw)	6	84	25.498	25.498
	ADT (Pedestrian)	200	401	69.678	69.678
	Train Speed (m/sec)	6	13	1.725	1.725
	No of trains	8	10	0.747	0.747
	Train visibility (meters)	800	1000	81.759	81.759
	ARG (%)	0	0	0.000	0.000
	PCR	1	5	1.650	1.650
	Number of lanes	1	1	0.000	0.000
	Road width (meters)	3	4	0.496	0.496
	Number of tracks	1	1	0.000	0.000
	Crossing angle(degrees)	-55	90	49.427	49.427
	Track gradient	0	0	.000	0.000
	Social awareness (Yes-1/No-1)	1	1	.000	0.000
	Driving style (Non-Agressive-1, Aggressive-0)	0	1	0.489	0.489
	Licensed (Yes-1,No-0)	0	1	0.485	0.485
	Impairment (Yes-1,No-0)	0	1	0.269	0.269
	Literate (Yes-1, No-0)	0	1	0.499	0.499
	Road vehicle speed (m/sec)	2.70	8.03	1.08263	1.08263
	Road sign board presence	1	1	0.000	0.000
	Number of tracks	1	1	0.000	0.000

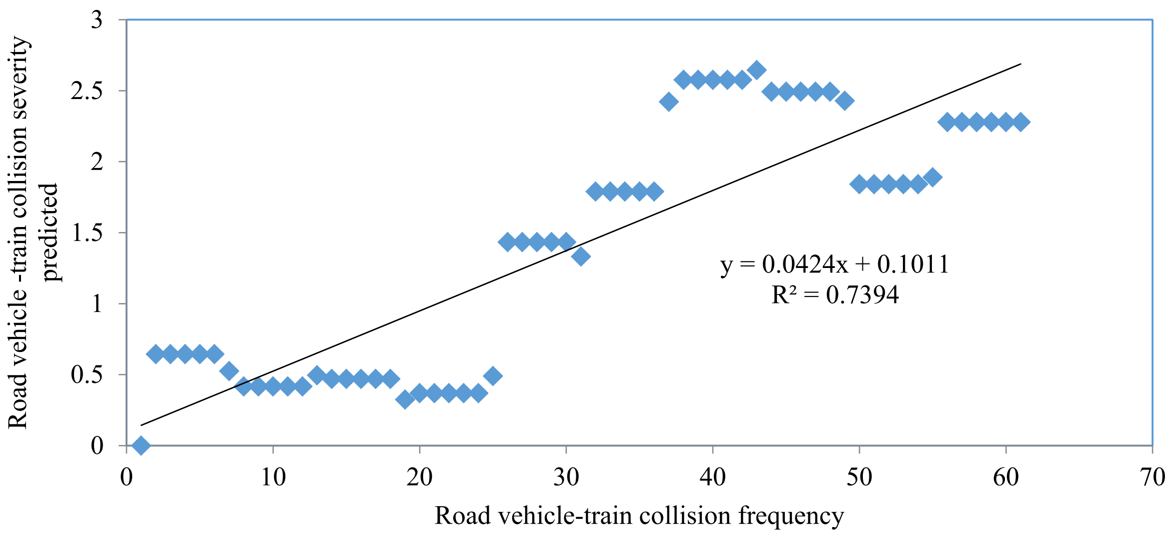

FIGURE 3. Road vehicle- train collision severity vs. Road vehicle- train collision severity predicted.

TABLE 8. The goodness of fit for Poisson-identity and Poisson-log road vehicle- train collision frequency prediction model.

	Poisson identity model			Poisson-log model		
	Value	df	Value /df	Value	Df	Value/df
Deviance	13.698	147	.093	11.525	147	.078
Scaled deviance	13.698	147		11.525	147	
Pearson Chi-Square	13.141	147	.089	11.191	147	.076
Scaled Pearson chi-square	13.141	147		11.191	147	
Log-Likelihood	-194.22			-193.14		
AIC	428.44			426.27		
AICC	434.19			432.01		
BIC	490.80			488.63		
CAIC	510.80			508.63		

TABLE 9. The goodness of fit for poisson power (2nd degree) model road vehicle- train collision frequency prediction model.

Poisson power (2nd degree) model			
	Value	df	Value/df
Deviance	15.882	147	0.108
Scaled deviance	15.882	147	
Pearson Chi-Square	15.175	147	0.103
Scaled Pearson chi-square	15.175	147	
Log-Likelihood	-195.314		
AIC	430.629		
AICC	436.382		
BIC	492.988		
CAIC	512.988		

TABLE 10. The goodness of fit for road vehicle- train collision severity prediction model.

Gamma-log model			
Deviance	Value	df	Value/df
Scaled deviance	8.253	149	.055
Pearson Chi-Square	168.364	149	
Scaled Pearson chi-square	7.612	149	.051
Log-Likelihood	155.293	149	
AIC	-32.288		
AICC	102.576		
BIC	107.746		
CAIC	161.818		

increase of rank based on road vehicle-train collision rate compared to rank based on road vehicle-train collision frequency.

B. SENSITIVITY ANALYSIS

The sensitivity analysis of AI-empowered road vehicle-train collision frequency modeling results revealed that, if train visibility decrease reaches 20%, the Poisson-identity road vehicle- train collision frequency model is predicted to increase by 172%. If crossing angle is increased to 460%, the Poisson-identity road vehicle- train collision frequency is predicted to increase to 163%, while Poisson-log road vehicle- train collision frequency model is predicted to increase to 99% and Poisson-power (2nd degree) road vehicle-train collision frequency models tend to increase the road vehicle- train collision frequency to 4%.

C. RISK EVALUATION BASED ON POISSON FREQUENCY AND GAMMA_LOG SEVERITY MODEL

The risk is defined by [31] is being calculated by multiplying the predicted frequency values based on Poisson models with predicted severity values based on the gamma-log model as

TABLE 11. Percentage (%) change rank based on road vehicle-train collision frequency and train collision rate.

Unmanned railway level crossing road vehicle-train collision location	Road-vehicle collision frequency	Rank based on road vehicle-train collision frequency	Road-vehicle collision rate	Rank based on road vehicle-train collision rate	% Change (road vehicle-train collision frequency vs. road vehicle-train collision rate)	Std. deviation (road vehicle-train collision frequency vs. road vehicle-train collision rate)
14-C	0.4	1	17.38	7	-86%	4.2
16-C	0.4	2	11.96	11	-82%	6.4
17-C	0	19	0	19	0%	0.0
21-C	0.2	8	16.42	9	-11%	0.7
34-C	0.4	3	32.02	3	0%	0.0
35-C	0.2	9	17.02	8	13%	0.7
43-C	0.2	10	10.08	16	-38%	4.2
50-C	0.4	4	34.29	2	100%	1.4
67-C	0.2	11	14.4	10	10%	0.7
72-C	0.4	5	23.35	5	0%	0.0
82-C	0.2	12	11.25	13	-8%	0.7
87-C	0.2	13	9.26	18	-28%	3.5
93-C	0.2	14	11.21	14	0%	0.0
103-C	0.2	15	10.78	15	0%	0.0
110-C	0.2	16	11.78	12	33%	2.8
122-C	0.4	6	28.44	4	50%	1.4
133-C	0.4	7	39.94	1	600%	4.2
136-C	0.2	17	9.53	17	0%	0.0
140-C	0.2	18	19.54	6	200%	8.5

shown in Table 12. The risk analysis revealed that road-vehicle train collision risk has been predicted to be 3.52 times higher on risk has been predicted to be 3.52 times higher on C-140 and lowest risk (C-87) has been observed to be 77% lower than average risk at all unmanned railway level crossings in direction 1. While, in direction 2, C-136 is 2.95 times higher and C-87 has 80% lower predicted risk than average risk at all unmanned railway level crossings.

D. MARGINAL EFFECT ANALYSIS

Individual road vehicle-train collision frequency and severity prevention countermeasure here is done by the use of CMF [32]–[34]. The CMF here uses prevention factors for both significant Poisson road vehicle-train collision frequency prediction and therefore reduces collisions [35]. CMF is the ratio of the predicted number of collisions after countermeasure application over a predicted number of collisions before the countermeasure application.

1. When CMF is implemented on the train visibility Poisson-log road vehicle-train collision frequency prediction model component, there is an 87.4 % decline in road vehicle-train collision frequency.
2. With CMF implementation on crossing angle component of the Poisson-log road vehicle-train collision frequency prediction model, there is an 89.9% decrease in road vehicle-train collision frequency.

Table 13 shows the individual CMF implemented an AI-based road vehicle- train collision frequency prediction model.

When road vehicle- train collision severity countermeasure is applied on gamma-log road vehicle-train collision severity prediction model significant parameters according to Table 14.

Table 14 shows the individual CMF implemented an AI-empowered road vehicle- train collision severity prediction model. ADT (Mini Bus/Bus) tends to decrease road vehicle- train collision severity to 85.7%, ADT (Scooter/Motor Cycle) countermeasure tends to decrease road vehicle- train collision severity to 89.59% (approx.), ADT (Rickshaw) tends to decrease it to 82.4% (approx.), train speed decreases road vehicle- train collision severity to 85.8% (approx.), the number of trains changes by countermeasure tends to reduce it to 84.7% (approx.) respectively. Train visibility, PCR, road width, and crossing angle countermeasure tends to decrease road vehicle- train collision severity by

TABLE 12. Risk evaluation based on poisson frequency and Gamma-log severity model.

Unmanned railway level crossing (Direction1- D1, Direction 2-D2)	Road vehicle-train collision Poisson- log frequency prediction model	Road vehicle-train collision Poisson-log frequency prediction model	Predicted risk-based on Poisson-log prediction model	Predicted risk-based on a Poisson power prediction model
14-C	12	1.1049	13.287	137.56
16-C	12	1.3659	16.425	170.05
17-C	12	1.4448	17.373	179.87
21-C	12	1.5472	18.605	192.63
34-C	5.27	0.8512	4.4859	47.921
35-C	5.27	0.7592	4.0006	42.736
43-C	5.27	0.6796	3.5815	38.259
50-C	5.27	0.6135	3.2329	34.536
67-C	6.7	1.1087	7.4272	85.952
72-C	6.7	1.0785	7.2255	83.617
82-C	5.77	0.6048	3.4874	39.73
87-C	5.77	0.6995	4.0334	45.951
93-C	8.26	1.0672	8.8198	93.154
103-C	8.26	1.2175	10.062	106.27
110-C	8.26	1.0382	8.5801	90.622
122-C	8.26	1.2259	10.132	107.01
133-C	10.4	1.3208	13.739	148.6
136-C	10.4	1.2734	13.246	143.26
140-C	10.4	2.0067	20.874	225.77
14-C	10.4	1.6278	16.933	183.15
16-C	4.65	0.9177	4.268	48.745
17-C	4.65	0.9023	4.1961	47.924
21-C	3.45	0.4882	1.6821	16.927
34-C	3.45	0.773	2.6632	26.799
35-C	7.48	0.9862	7.3751	86.272
43-C	7.48	0.6129	4.5834	53.616
50-C	7.48	0.5986	4.4762	52.362
67-C	7.48	0.7618	5.6967	66.639
72-C	5.7	0.6438	3.6571	78.453
82-C	5.7	0.4165	2.3658	50.751
87-C	5.7	0.469	2.6639	57.146
93-C	5.7	0.3693	2.0976	44.997
103-C	8.1	1.4328	11.665	232.39
110-C	8.1	1.7886	14.562	290.1
122-C	7.2	2.576	18.601	383.59
133-C	7.2	2.4926	17.999	371.18
136-C	11.2	1.8409	20.537	370.18
140-C	11.2	2.2781	25.415	458.1

TABLE 13. Individual CMF implemented road vehicle- train collision frequency prediction model.

Road vehicle-train collision frequency countermeasure	Train Visibility	Crossing angle
Coefficient	-0.003	0.005
Increase/Reduction factor	8.800	0.250
CMF	0.974	0.999

TABLE 14. Individual CMF implemented a gamma-model road vehicle- train collision severity prediction model.

Road vehicle-train collision severity countermeasure	ADT minibus/bus (veh/ day)	ADT scooter/ motorcycle (veh/ day)	ADT rickshaw (veh/ day)	Train speed (veh/ day)	Number of trains	Train visibility (m/sec)	PCR	Road width (meters)	Crossing angle (degrees)
Coefficient	-0.005	0.001	-0.006	0.074	-0.219	-0.003	0.07	-0.330	0.004
Increase/ Reduction factor	8.800	4.140	13.170	0.58	0.25	0.25	0.8	0.40	0.82
CMF	0.957	0.996	0.924	0.96	0.95	0.99	0.9	0.88	0.99

89.92% (approx.), 84.93% (approx.), 77.64 %(approx.) and 89.68 % (approx.) respectively.

VI. CONCLUSION AND FUTURE RESEARCH OPPORTUNITIES

A. CONCLUSION

In this paper, the road vehicle-train collision risk prediction assessment model based on AI has been developed for accident avoidance of road vehicles approaching the unmanned railway level crossings. These vehicles are under a high risk of collisions with passing trains over the crossings. To alleviate this problem, a road vehicle-train collision risk prediction assessment has been performed by collision frequency and severity prediction modeling using Poisson and Gamma-log regression techniques respectively. The rank analysis conducted based on road vehicle-train collision rate revealed that approximately 68% of the crossings predicted a rise in the rank as compared to accident frequency and it tends to decrease on remaining number of crossings. Further, the sensitivity analysis revealed that train visibility and crossing angle are the highest contributing factors in risk escalation of road vehicle-train collisions at these crossings. The risk analysis revealed that road-vehicle train collision risk has been predicted to be 3.52 times higher and 77% (approx.) lower in one direction whereas, in other direction, it is 2.95 times higher and 80% (approx.) lower than average risk assessed at all unmanned railway level crossings. Thereafter, the marginal effect analysis indicates that using collision modification factor implementation on 'crossing angle' and 'train visibility', it predicts to reduce the road vehicle-train collision risk to 85% approximately. Therefore, the presented model is a good solution to provide reliable risk assessment prediction for avoiding road vehicle-train collisions at unmanned railway level crossings.

B. FUTURE RESEARCH OPPORTUNITIES

The future research opportunities that may help in the improvement of the road risk assessment and avoidance are

1. The methodology can be extended to different climatic conditions (like heavy fog conditions).
2. Use of AI-empowered road vehicle- train collision risk prediction assessment model can be extended to multiple railway line sections
3. Web-based software development or AI implementation technique like clustering for accident hotspot identification at unmanned railway level crossings.

REFERENCES

[1] United Nations US. (2000). *Evaluation of Cost-Effective Systems for Railway Level-Crossing Protection*. [Online]. Available: https://www.unescap.org/sites/default/files/level-crossing-fulltext.pdf

[2] A. Kumar and S. Garg, "Efforts of Indian Railways to reduce level crossing accidents," in *Proc. Global Level Cross. Saf. and Tres. Prev. Symp.*, 2014.

[3] S. Gakkhar and B. Panchal, "A review on accident prevention methods at railway line crossings," *Int. Res. J. Eng. Technol.*, vol. 5, no. 4, pp. 1102–1107, 2018.

[4] *Indian Railways India, Budget, Speech of Shri D.V. Sadananda Gowda. In: Railway Budget*. Accessed: Jul. 8, 2014. [Online]. Available: http: www.ibef.org/download/English-Railway-Budget-Speech-2014-15.pdf

[5] V. Gitelman and A. S. Hakkert, "The evaluation of road-rail crossing safety with limited accident statistics," *Accident Anal. Prevention*, vol. 29, pp. 171–179, Mar. 1997, doi: 10.1016/S0001-4575(96)00069-3.

[6] R. T. Anderson and C. P. L. Barkan, "Railroad accident rates for use in transportation risk analysis," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1863, no. 1, pp. 88–98, Jan. 2004, doi: 10.3141/1863-12.

[7] J. Lee, D. Nam, and D. Park, "Analyzing the relationship between grade crossing elements and accidents," *J. Eastern Asia Soc. Transp. Stud.*, vol. 6, pp. 3658–3668, Jan. 2005.

[8] S. C. Mok and I. Savage, "Why has safety improved at rail-highway grade crossings?" *Risk Anal.*, vol. 25, no. 4, pp. 867–881, Aug. 2005, doi: 10.1111/j.1539-6924.2005.00642.x.

[9] J. Oh, S. P. Washington, and D. Nam, "Accident prediction model for railway-highway interfaces," *Accident Anal. Prevention*, vol. 38, no. 2, pp. 346–356, Mar. 2006, doi: 10.1016/j.aap.2005.10.004.

[10] A. Ahamed, N. Islam, M. A. S. Soikot, M. S. Hossen, R. Ahmed, and M. A. Hasan, "Train collision avoidance using GPS and GSM module," in *Proc. Int. Conf. Power Electron., Control Autom. (ICPECA)*, Nov. 2019, doi: 10.1109/ICPECA47973.2019.8975543.

[11] C. Lee, "Accident risk at a railway level crossing," *J. Eastern Asia Soc. Transp. Stud.*, vol. 7, pp. 53–61, 2007, doi: 10.11175/eastpro.2007.0.8.0.

[12] *Railroad-Highway Grade Crossing Handbook-Revised*, 2nd ed., Federal Highway Administration US, Washington, DC, USA, Report for US DOT, 2007. Accessed: Aug. 2007. [Online]. Available: https://www.ite.org/pub/?id=e1c1d474-2354-d714-518d-54feff533560/
[13] G. M. McCollister and C. C. Pflaum, "A model to predict the probability of highway rail crossing accidents," *Proc. Inst. Mech. Eng., F, J. Rail Rapid Transit*, vol. 221, no. 3, pp. 321–329, May 2007, doi: 10.1243/09544097JRRT84.
[14] S.-R. Hu and K.-H. Wu, "Accident risk analysis and model applications of railway level crossings," in *Proc. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2008, pp. 687–692, doi: 10.1109/ITSC.2008.4732661.
[15] S.-R. Hu, C.-S. Li, and C.-K. Lee, "Assessing casualty risk of railroad-grade crossing crashes using zero-inflated Poisson models," *J. Transp. Eng.*, vol. 137, no. 8, pp. 527–536, 2011, doi: 10.1061/(ASCE)TE.1943-5436.0000243.
[16] W. Hao and J. R. Daniel, "Severity of injuries to motor vehicle drivers at highway–rail grade crossings in the United States," *Transp. Res. Rec.*, pp. 102–108, Jan. 2013, doi: 10.3141/2384-12.
[17] W. Hao and J. Daniel, "Driver injury severity related to inclement weather at highway–rail grade crossings in the United States," *Traffic Injury Prevention*, vol. 17, pp. 31–38, Feb. 2016, doi: 10.1080/15389588.2015.1034274.
[18] S.-R. Hu, C.-S. Li, and C.-K. Lee, "Investigation of key factors for accident severity at railroad grade crossings by using a logit model," *Saf. Sci.*, vol. 48, pp. 186–194, Feb. 2010, doi: 10.1016/j.ssci.2009.07.010.
[19] W. Zheng, J. R. Mueller, R. Slovak, and E. Schnieder, "Function modelling and risk analysis of automated level crossing based on national statistical data," in *Proc. 2nd Int. Asia Conf. Informat. Control, Autom. Robot. (CAR)*, Wuhan, China, Mar. 2010, pp. 281–284, doi: 10.1109/CAR.2010.5456546.
[20] D. Chen and R. Cheng, "Incremental train control system of Qinghai–Tibet railway," in *Intelligent Processing Algorithms and Applications for GPS Positioning Data of Qinghai-Tibet Railway*. Berlin, Germany: Springer, 2019, pp. 35–50.
[21] T. Tjahjono, A. Kusuma, Y. Y. Pratiwi, and R. Y. Purnomo, "Identification determinant variables of the injury severity crashes at road-railway level crossing in Indonesia," *Transp. Res. Procedia*, vol. 37, pp. 211–218, Jan. 2019, doi: 10.1016/j.trpro.2018.12.185.
[22] P. McCullagh and J. A. Nelder, *Generalized Linear Model*, 2nd ed. New York, NY, USA: CRC Press, 1989.
[23] O. V. Sabnis and L. R., "A novel object detection system for improving safety at unmanned railway crossings," in *Proc. 5th Int. Conf. Sci. Technol. Eng. Math. (ICONSTEM)*, vol. 1, Mar. 2019, pp. 149–152, doi: 10.1109/ICONSTEM.2019.8918786.
[24] V. Singhal, S. S. Jain, and M. Parida, "Train sound level detection system at unmanned railway level crossings," *Eur. Transp./Trasporti Europei*, vol. 68, no. 3, pp. 1–18, Jun. 2018.
[25] P. Mittal, V. Singhal, and P. S. S. Jain, "ICT enabled vehicular safe distance modeling at Indian unmanned railway level crossings," *SSRN Electron. J.*, pp. 3–6, Apr. 2019, doi: 10.2139/ssrn.3350321.
[26] P. D. Allison, "SAS global forum," Paper 1485-2014, 2014, vol. 2, pp. 1–13.
[27] J. D. Singer and J. B. Willett, *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. London, U.K.: Oxford Univ. Press, 2003.
[28] K. P. Burnham and D. R. Anderson, *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*, 2nd ed. London, U.K.: Springer-Verlag, 2002.
[29] H. Akaike, "A new look at the statistical model identification," *IEEE Trans. Autom. Control*, vol. 19, no. 6, pp. 716–723, Dec. 1974, doi: 10.1109/TAC.1974.1100705.
[30] J. E. Cavanaugh, "Unifying the derivations for the Akaike and corrected Akaike information criteria," *Statist. Probab. Lett.*, vol. 33, pp. 201–208, Apr. 1997, doi: 10.1016/s0167-7152(96)00128-9.
[31] B. M. Ayyub, *Risk Analysis in Engineering and Economics*, 2nd ed. New York, NY, USA: CRC Press, 2003.
[32] J. C. Laughland, L. E. Haefner, J. W. Hall, and D. R. Clough, "Methods for evaluating highway safety improvements," *Transp. Res. Rec.*, pp. 1–150, 1975.
[33] Z. Ning, Y. Li, P. Dong, X. Wang, M. S. Obaidat, X. Hu, L. Guo, Y. Guo, J. Huang, and B. Hu, "When deep reinforcement learning meets 5G-enabled vehicular networks: A distributed offloading framework for traffic big data," *IEEE Trans. Ind. Informat.*, vol. 16, no. 2, pp. 1352–1361, Feb. 2020.
[34] Z. Ning, P. Dong, X. Wang, X. Hu, L. Guo, B. Hu, Y. Guo, T. Qiu, and R. Y. K. Kwok, "Mobile edge computing enabled 5G health monitoring for Internet of medical things: A decentralized game theoretic approach," *IEEE J. Sel. Areas Commun.*, to be published.
[35] Z. Ning, K. Zhang, X. Wang, M. S. Obaidat, L. Guo, X. Hu, B. Hu, Y. Guo, B. Sadoun, and R. Y. K. Kwok, "Joint computing and caching in 5G-envisioned Internet of vehicles: A deep reinforcement learning-based traffic control system," *IEEE Trans. Intell. Transp. Syst.*, early access, Feb. 5, 2020, doi: 10.1109/TITS.2020.2970276.

VIVEK SINGHAL received the Ph.D. degree from the Indian Institute of Technology (IIT) Roorkee, India. He is currently an Associate Professor with the Department of Information Technology, JSS Academy of Technical Education, Noida, India. He has over eight years of teaching and research experience and has published around several research articles and articles in refereed journals. His main research interests are artificial intelligence, machine learning, intelligent transportation systems, and multi-agent systems and its application to medicine.

S. S. JAIN is currently a retired Professor with the Transportation Engineering Group, Department of Civil Engineering, and an Associate Faculty with the Centre for Transportation Systems (CTRANS), Indian Institute of Technology Roorkee. He has contributed over 430 research articles in Indian and Foreign Journals and Conference Proceedings. He has completed 32 sponsored research projects, including three nationally coordinated projects on Urban Transport Environment Interaction, Road Traffic Safety, and Integrated Development of Public Transport System.

Dr. Jain had been a member, Editorial Board of Institution of Civil Engineers (UK) Journal. He is also a member of various Technical Committees of Indian Roads Congress and Member, World Roads Congress, Technical Committee, PIARC, France. He is a Fellow of Institution of Engineers, India, and a Fellow of Indian Institution of Bridge Engineers. He was a recipient of 42 Medals/Prizes/Awards which includes University Gold Medal, Khosla Research Prizes and Medals, First Recipient of Jawahar Lal Nehru Award from Indian Roads Congress, Present of India Prize from Institution of Engineers, U.P. Government National Award from Indian Society for Technical Education, Prof. S. R. Mehra National Award.

DIVYA ANAND is currently an Assistant Professor with the School of Computer Science and Engineering, Lovely Professional University, India. She has over two years of research experience. Her areas of interest include expert systems and artificial intelligence.

AMAN SINGH is currently working as an Assistant Professor of computer science and engineering with Lovely Professional University, India. He has about seven years of teaching experience and his areas of interests are biomedical engineering, medical expert systems, artificial intelligence in medicine, and health information systems. He has published scientific research publications in reputed international/national journals and conferences, which are indexed in various international databases. He is invited as a Faculty Resource Person/Session Chair/Reviewer/TPC member in different FDP, conferences, and journals.

SAHIL VERMA (Member, IEEE) received the B.Tech. and M.Tech. degrees from Maharishi Markandeshwar University, Mullana, India, in 2012, and the Ph.D. degree from Jaipur National University, Jaipur, India, in 2017, all in computer science and engineering. He is currently working as an Associate Professor with Lovely Professional University, Phagwara, India. He has many research contributions in the area of cloud computing, the Internet of Things, vehicular *Ad-hoc* networks, WSN, and MANET. Some of his research findings are published in top-cited journals, such as IEEE, Wiley. Various international conferences of repute. He is a member of ACM and IAENG, and an Editorial Board Member of many international journals. He has chaired many sessions in reputed international conferences abroad and India. He has guided 14 P.G students and three Ph.D. students and six are ongoing. He has visited many universities in abroad and India.

KAVITA (Member, IEEE) received the B.Tech. and M.Tech. degrees from Maharishi Markandeshwar University, Mullana, India, in 2012, and the Ph.D. degree from Jaipur National University, Jaipur, India, in 2018, all in computer science and engineering. She is currently working as an Associate Professor with Lovely Professional University, Phagwara, India. She has many research contributions in the area of cloud computing, the Internet of Things, vehicular *ad-hoc* networks, WSN, and MANET. Some of her research findings are published in top-cited journals, such as IEEE, Wiley. Various international conferences of repute. She is a member ACM and IAENG, and an Editorial Board Member of many international journals. She has chaired many sessions in reputed international conferences abroad and India. She is guiding six Ph.D. students. She has visited many universities out of these two are international universities (Italy and the Czech Republic).

JOEL J. P. C. RODRIGUES (Fellow, IEEE) is currently a Professor with the National Institute of Telecommunications (Inatel), Brazil, a Senior Researcher with the Instituto de Telecomunicações, Portugal, and a Visiting Professor with the Federal University of Piauí, Brazil. He has authored or coauthored over 850 papers in refereed international journals and conferences, three books, and two patents. He is a member of many international TPCs and participated in several international conferences organization. He is a licensed Professional Engineer (as a Senior Member), a member of the Internet Society, and a Senior Member of ACM. He had received several Outstanding Leadership and Outstanding Service Awards by the IEEE Communications Society and several best papers awards. He is also the Leader of the Internet of Things research group (CNPq), the Director for Conference Development - IEEE ComSoc Board of Governors, an IEEE Distinguished Lecturer, the Technical Activities Committee Chair of the IEEE ComSoc Latin America Region Board, the President of the scientific council at ParkUrbis–Covilhã Science and Technology Park, the Past-Chair of the IEEE ComSoc Technical Committee on eHealth, the Past-Chair of the IEEE ComSoc Technical Committee on Communications Software, a Steering Committee member of the IEEE Life Sciences Technical Community and Publications Co-Chair, and a member Representative of the IEEE Communications Society on the IEEE Biometrics Council. He has been the General Chair and the TPC Chair of many international conferences, including IEEE ICC, IEEE GLOBECOM, IEEE HEALTHCOM, and IEEE LatinCom. He is the Editor-in-Chief of the *International Journal on E-Health and Medical Communications* and an editorial board member of several high-reputed journals.

NOOR ZAMAN JHANJHI (Senior Member, IEEE) is currently working as an Associate Professor with Taylor's University, Malaysia. He has great international exposure in academia, research, administration, and academic quality accreditation. He worked with ILMA University, and King Faisal University (KFU) for a decade. He has 20 years of teaching & administrative experience. He has an intensive background of academic quality accreditation in higher education besides scientific research activities, he had worked a decade for academic accreditation and earned ABET accreditation twice for three programs at CCSIT, King Faisal University, Saudi Arabia. He also worked for National Commission for Academic Accreditation and Assessment (NCAAA), Education Evaluation Commission Higher Education Sector (EECHES) formerly NCAAA Saudi Arabia, for institutional level accreditation. He also worked for the National Computing Education Accreditation Council (NCEAC). He has awarded as top reviewer 1% globally by WoS/ISI (Publons) recently for the year 2019. He has edited/authored more than 13 research books with international reputed publishers, earned several research grants, and a great number of indexed research articles on his credit. He has supervised several postgraduate students, including master's and Ph.D. Dr. Jhanjhi is an Associate Editor of IEEE ACCESS, a moderator of IEEE TechRxiv, a Keynote speaker for several IEEE international conferences globally, an External Examiner/Evaluator for Ph.D. and masters for several universities, a Guest Editor of several reputed journals, a member of the editorial board of several research journals, and an Active TPC Member of reputed conferences around the globe.

UTTAM GHOSH (Senior Member, IEEE) received the Ph.D. degree in electronics and electrical engineering from the Indian Institute of Technology Kharagpur, India, in 2013. He was a Postdoctoral Experience with the University of Illinois in Urbana-Champaign, Fordham University, and Tennessee State University. He is currently working as an Assistant Professor of the practice with the Department of Electrical Engineering and Computer Science, Vanderbilt University, Nashville, TN, USA. He has published 55 articles at reputed international journals, including the IEEE TRANSACTION, Elsevier, Springer, IET, Wiley, InderScience, and IETE, and also in top international conferences sponsored by IEEE, ACM, and Springer. His main research interests include cybersecurity, computer networks, wireless networks, information-centric networking, and software-defined networking. Dr. Ghosh is a member of AAAS, ASEE, ACM, and Sigma Xi. He is actively working for editing two edited volumes on Emerging CPS, Security, Machine / Machine Learning with CRC Press, Chapman Hall Big Data Series.

OHYUN JO (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical engineering from the Korea Advanced Institute of Science and Technology (KAIST), in 2005, 2007, and 2011, respectively. From April 2011 to February 2016, he was with Samsung Electronics Company Ltd., in charge of research and development for future wireless communication systems, applications, and services. From March 2016 to July 2017, he was a Senior Researcher with the Electronics and Telecommunications Research Institute (ETRI), and from August 2017 to February 2018, he was an Assistant Professor with the Department of Electrical Engineering, Korea Military Academy. He is currently an Assistant Professor with the Department of Computer Science, Chungbuk National University. His research interests include millimeter-wave communications, next-generation WLAN/WPAN systems, 5G mobile communication systems, military communications, the Internet of Things, future wireless solutions/applications/services, machine learning, and embedded communications FPGA/ASIC design.

CELESTINE IWENDI (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical and electronics engineering, took courses in Scientific Computing, the second master's degree in communication hardware and microsystem engineering from Uppsala University, Sweden, and the Ph.D. degree in electronics from the University of Aberdeen, U.K., in 2013. He is currently an Associate Professor from Sweden. A highly motivated researcher with a wireless sensor network security book, and over 100 publications. He is passionate about the teaching and mentoring of students at the undergraduate, Masters, and Doctoral levels. A teacher with an emphasis on communication, hands-on experience, willing-to-learn, and 18 years research, teaching, technical expertise and currently teaches Engineering team Project, Circuit Theory, Data Network, and Distributed Systems, Wireless Sensor Networks, IoT Security, Artificial Intelligence with sensor applications, Mathematics, Computer Engineering, and Control Systems. He has developed operational, maintenance, and testing procedures for electronic products, components, equipment, and systems; provided technical support and instruction to staff and customers regarding equipment standards, assisting with specific, difficult in-service engineering; Inspected electronic and communication equipment, instruments, products, and systems to ensure conformance to specifications, safety standards, and regulations. He is a wireless sensor network Chief Evangelist, a Researcher, and a Designer. His research interests include wireless sensor networks, security of things (SoT), communication controls, the Internet of Things (IoT), deep neural networks, artificial intelligence involving wireless sensor networks, control of electrical machines, business IT, 5G networks, and low power communication protocols. Dr. Iwendi is also a Board Member of the IEEE Sweden Section. He is a Chartered Engineer and a Fellow of The Higher Education Academy, the United Kingdom that involves a pedagogical program development. He is the Co-Chair of the special session on Wireless Sensor Networks: Hardware/Software Design aspects for Industry at the Prestigious International Conference of Industrial Technology (ICIT). He was an Editor of the International Journal of Engineering and Allied Disciplines, in 2015, a Newsletter Editor of the IEEE Sweden section, in 2017, the Editor-in-Chief of *Wireless Sensor Network Magazine*, in 2009, a Committee Member of the International Advisory Panel, the International Conference on Marine, Ocean and Environmental Sciences and Technologies (MAROCENET), from 2014 to 2016, the Editor-in-Chief of the *Journal of Wireless Sensor Network*, in 2009, and an Advisory Board of the *International Journal of Innovative Computer Science and Engineering* (IJICSE), in 2013.