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

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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.
respectively [1]. The railway level crossings contribute 43% (50 out of 117) of all consequential train accidents and 67% fatalities (101 out 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 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 unmanned railway level 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 model 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)-

\[
Pr(der) = \sum R_i m_i
\]

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
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 rises 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-Shamlip-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 chaining 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, minitruck/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 (2nd degree). The Poisson-identity, Poisson-log, and Poisson power (2nd degree) models are shown in Eqns. (2) to (4).

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

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

Model C:
$$ y_{Poisson-Power(2)} = (-0.014 \times \text{Train Visibility} + 0.019 \times \text{Crossing Angle} + 20.933)^2 \quad (4) $$
| S. No. | Unmanned Railway Level Crossing | Road passing over unmanned railway level crossing | 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 Sunhera to Khekra        | 3.541                                                         |
| 5     | 34-C Baraut-Baghpat (BU-TPM)    | Saroorpur Kalan to Gaadhi Saroorpur Kalan to Khekra | 4.293                                                         |
| 6     | 35-C Baraut-Baghpat (BU-BPM)    | Saroorpur Kalan to Sujra Sujra to Saroorpur Kalan | 3.222                                                         |
| 7     | 43-C Baraut-Baghpat (BU-BPM)    | Irdispur to Badka Irdispur to Badka             | 1.669                                                         |
| 8     | 50-C Baraut-Quasimpur Kheri (BU-KPKI) | Baoli to Latifpur 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-SMLQ)  | PanjaKhara to Jasala Jasala to PanjaKhara       | 1.135                                                         |
| 12    | 87-C Kandhla-Shamli (KQL-SMLQ)  | 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 Thanabhwana-Nanauta (THBN-NNX) | Ambeta YakubPur to Jalabad Jalab to Ambeta | 3.448                                                         |
| 16    | 122-C Rampur Manihar-Nanauta (RPMN-NNX) | Tipra to Sambhalkheri Sambhalkheri to Tipra | 2.624                                                         |
| 17    | 133-C Rampur manihar-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                      |

\[ Y_{\text{Poisson-identity}} = \text{Road vehicle-train Poisson-identity collision frequency Poisson prediction output variable} \]

\[ Y_{\text{Poisson-log}} = \text{Road vehicle-train Poisson collision frequency prediction output variable Poisson prediction output variable} \]

\[ Y_{\text{Poisson-power(2)}} = \text{Road vehicle-train Poisson-power (2\text{nd degree}) collision frequency Poisson prediction output variable.} \]

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

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).

\[ y_{gm} = \exp(4.725 - 0.005 \times \text{ADT (MiniBus/Bus)} + 0.001 \times \text{ADT (Scooter/Motorcycle)} - 0.006 \times \text{ADT (Rickshaw)} + 0.074 \times \text{Train Speed} - 0.219 \times \text{Number of Trains} - 0.003 \times \text{Train Visibility} + 0.065 \times \text{PCR} - 0.33 \times \text{Road Width} + 0.004 \times \text{Crossing Angle}) \]
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                                  |
| 34-C                            | 0 0%    | 0 0%    | 5 0%    | 7                                  |
| 35-C                            | 2 0%    | 0 0%    | 5 31%   | 7                                  |
| 43-C                            | 0 17%   | 0 0%    | 1 31%   | 1                                  |
| 50-C                            | 0 0%    | 2 0%    | 0 6%    | 0                                  |
| 67-C                            | 0 25%   | 0 22%   | 0 0%    | 0                                  |
| 72-C                            | 0 0%    | 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%    | 22% 0%  | 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 (2nd 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 (2nd 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-train 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...
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.

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

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

| Dependent variable (s) | Minimum | Maximum | Mean    | Std. dev. |
|------------------------|---------|---------|---------|-----------|
| Road vehicle-train collision (2009-13) | 1       | 3       | 0.625   | 0.625     |
| 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    | .000      |
| Social awareness       | 1       | 1       | .000    | .000      |
| (Yes-1/No-1)           | 0       | 1       | 0.489   | 0.489     |
| Driving style          | 0       | 1       | 0.485   | 0.485     |
| (Non-Agressive-1, Aggressive-0) | 0    | 1      | 0.485   | 0.485     |
| Licensed               | 0       | 1       | 0.269   | 0.269     |
| Impairment             | 0       | 1       | 0.499   | 0.499     |
| (Yes-1, No-0)          | 0       | 1       | 0.1011  | 0.7394    |
| Literate               | 0       | 1       | 0.000   | 0.000     |
| (Yes-1, No-0)          | 0       | 1       | 0.000   | 0.000     |
| 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.](image-url)
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 |     |          |
| AICCC                  | 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|    |          |
| AICCC                            | 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 | Value | df | Value/df |
|-----------------|-------|----|----------|
| Deviance        | Value | df | Value/df |
| Scaled deviance | 8.253 | 149| .055     |
| Pearson Chi-Square | 168.364| 149| .051     |
| Scaled Pearson chi-square | 7.612 | 149| .051     |
| Log-Likelihood  | 155.293| 149|          |
| AIC             | -32.288|   |          |
| AICCC           | 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
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

| 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 | 0.0 | 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 |
| Unmanned railway level crossing (Direction 1: 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                                                       | 4.0066                                                       | 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                                                       |
| 87-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/shaw (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              | 0.04                     |
| 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 rank 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.

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