PEDESTRIAN SAFETY EVALUATION AT UNSIGNALIZED INTERSECTION USING PET AS SURROGATE SAFETY MEASURE

A Major Project submitted

In Partial Fulfilment of Requirements for the Degree

Of

BACHELOR OF TECHNOLOGY

IN

CIVIL ENGINEERING

Submitted By

ABHISHEK SHRIVASTAVA (18114003)
MOUNIKA CHEETAKALA (18114015)
NITISHA GUPTA (18114044)
TRIPTI YADAV (18114072)

FORWARDED BY

Dr. G. RAMTEKKAR
Head of the Department
Civil engineering Department

NIT Raipur (C.G.)

GUIDED BY

Dr. SUNNY DEOL G.
Assistant Professor
Civil engineering Department
NIT Raipur (C.G.)

2021-22

CIVIL ENGINEERING DEPARTMENT
NATIONAL INSTITUTE OF TECHNOLOGY RAIPUR
RAIPUR-492010
CHHATTISGARH, INDIA

CERTIFICATE

This is to certify that the work which is being presented in the B.Tech. Major Project entitled **"Pedestrian Safety Evaluation at Unsignalized Intersection Using PET as Surrogate Safety Measure"** in the partial fulfilment of the requirements for the award of the Bachelor of Technology in Civil Engineering and submitted to the Department of Civil Engineering of National Institute of Technology Raipur is a bona-fide record of their own work carried out under my supervision during academic session 2021-22.

This certification does not necessarily endorse or accept any statement made, opinion expressed, or conclusion drawn as recorded in this report. However, it only signifies the acceptance of report for the purpose of which it is submitted, also the matter presented in this report has not been submitted earlier by candidates for the award of any other degree elsewhere.

Candidates:

ABHISHEK SHRIVASTAVA (18114003)

MOUNIKA CHEETAKALA (18114015)

NITISHA GUPTA (18114044)

TRIPTI YADAV (18114072)

GUIDED BY:	**APPROVED BY:**
Dr. SUNNY DEOL G	Dr. G. RAMTEKKAR
Assistant Professor	Head of the Department
Department of Civil Engineering	Department of Civil Engineering
NIT Raipur	NIT Raipur

DECLARATION

We hereby declare that the Major project entitled **"Pedestrian Safety Evaluation at Unsignalized Intersection Using PET as Surrogate Safety Measure"** submitted to the partial fulfilment of requirement for the award of degree of bachelor of technology in civil engineering is our original work and the project has not formed the basis for the award of any other degree associate-ship, fellowship or any other similar titles.

We further affirm that the contents of this project shall neither be released to any media nor shall be published in any firm without the prior approval of our guide as well as the institution.

Candidates:

ABHISHEK SHRIVASTAVA (18114003)

MOUNIKA CHEETAKALA (18114015)

NITISHA GUPTA (18114044)

TRIPTI YADAV (18114072)

Place: RAIPUR
Date: April 30, 2022

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ABHISHEK SHRIVASTAVA (18114003)

MOUNIKA CHEETAKALA (18114015)

NITISHA GUPTA (18114044)

TRIPTI YADAV (18114072)

ABSTRACT

The port-to-port transfer of person or goods by a medium which can be a vehicle, or a person is known as Transportation. Pedestrians being one mode of transfer face the most difficult situation during the crossing near the intersection and mid-block sections, as they are the most ignored modes of transportation in terms of safety and facility. Pedestrian road safety is matter of concern looking at its gravity, magnitude, and impact associated with it. The intersections are mainly defined and designed dominantly for motorized vehicles only, but a high rate of pedestrian fatalities shows the need for explicit consideration of safety for the pedestrian. So, with time the pedestrian safety become an important aspect and primary goal of transportation. In developing country like India, the accuracy, and reliability of the available pedestrian-vehicle accident data are highly questionable, because the pedestrian-vehicle crash data are rarely reported, and for that, no standard data recording method is followed. So, due to unavailability of reliable and detailed accident records, quantification of pedestrian safety level is limited as compared to crash prediction models developed for vehicle conflicts. Therefore, more effective, and proactive safety evaluation technique is necessary for the evaluation. The objective of this study is to identify and propose a proactive safety measure- based technology to evaluate the safety of pedestrians at an unsignalized intersection in India. The major advantage of proactive safety indicator is the inclusion of conflict which is more frequent than the actual happening of accidents and hence the results are effective, statistically more significant, and are reliable measure of traffic safety. In this study, The Post Encroachment Time (PET) is used as a proximal surrogate safety indicator. The necessary pedestrian-vehicle conflicts were obtained from the videographic survey conducted at an unsignalized intersection in front of National Institute of technology Raipur, Chhattisgarh. The conflicts were grouped as highly severe conflict, severe conflict, and normal conflict according to the behaviour of the participants of the conflicts (pedestrian & vehicle), the threshold PET values of each conflict group were then obtained using two methods one is the Cumulative Distribution Frequency (CDF) technique and other obtained using Support Vector Machine (SVM) algorithm. This paper describes effect of the vehicle approaching speed on the severity of the conflict under non-lane-based mix traffic condition. Furthermore, it also establishes the threshold PET values for highly

severe conflict, severe conflict, and normal conflict which can be used for the prediction of severity of the conflicts in an unsignalized intersection.

In this paper the two methods for defining threshold are compared for their accuracy in terms of the observed classification and the classification based on the threshold values obtained from the two methods. It was found from the success prediction table that the SVM has accuracy of 76.47% and CDF has the accuracy of 64.7%, which implies that the SVM method is more reliable.

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1 Introduction

1.1 Back-ground

Road safety is a matter of national concern looking at its gravity, magnitude, and impact associated with it. The Global Status Report on Road Safety 2015 stated that in India, every year more than 207,551 people are killed in road traffic crashes. Out of which approximately half of the deaths are contributed by the most vulnerable road users - motorcyclists, pedestrians, and cyclists. As per this report, the unsafe road infrastructure, a vehicle with poor condition, and improper space management makes the heterogeneous traffic condition more hazardous, which leads towards the high fatality rates on the Indian road. Intersections are designed to provide and facilitate the smooth traffic movement in all the direction. While designing, the designer should allocate proper space and proportionate time to all traffic movement in efficient and safe manner. The intersections are mainly defined and designed dominantly for motorized vehicles only, but a high rate of pedestrian fatalities shows the need for explicit consideration of safety for the pedestrian. So, with time the pedestrian safety become an important aspect and primary goal of transportation. When the path of two road users crosses each other, conflict can happen between them at the point of crossing. Vehicle-Pedestrian conflicts are not acceptable as they are both evitable and predictable.

Usually, the safety analysis using conventional method is based on several years of crash data to understand the trend of the accidents and factors affecting it. In developing country like India, the accuracy, and reliability of the available pedestrian-vehicle accident data are highly questionable. Because the pedestrian-vehicle crash data are rarely reported, and for that, no standard data recording method is followed. So, due to unavailability of reliable and detailed accident records, quantification of pedestrian safety level is limited as compared to crash prediction models developed for vehicle conflicts. So, the proactive approach named "Conflict analysis" was drawn up to tackle the lack of historical data and exposure. In this method, traffic conflicts have been used as a measure of crash potential Amundsen and Hyden have defined the traffic conflict as "an observable situation in which two or more road users' approach toward each other in particular space and time to an extent where there is a risk of collision if their movements remained unchanged."

Instead of waiting for actual crashes to occur, the conflict approach can substitute actual crash numbers to develop a surrogate measure of safety. Surrogate safety measures are on basis of the idea that accidents change from conflicts, which are situations where the chance of a collision is high. In different studies, there are many surrogate safety indicators like Gap-Time (GT), Deceleration-Rate (DR), Proportion-of-Stopping-Distance (PSD), Time-To-Conflict (TTC), Post-Encroachment-Time (PET), and Time-To-Zebra (TTZ) were used to evaluate the safety. Van der Horst evaluated the safety of urban intersection in homogeneous traffic condition. He recorded various conflicts between car-pedestrian, car-car, and car-bicycle and derived the combined cumulative PET distribution for all conflicts. From this study, it was found that 15 th percentile PET 0.52 seconds, median PET as 1.39 seconds and mean PET as 1.43 seconds. In general, he concluded that conflict is having PET value less than I seconds as critical conflict and PET greater than 2 seconds as conflict Many researchers have developed the simulation models to evaluate the traffic safety using proximal safety indicators (surrogate safety measures) for vehicle- vehicle conflict. Few researchers have used the surrogate safety measures for the proactive safety evaluation of vehicle-vehicle conflict at an unsignalized intersection in mix traffic condition.

Many of the existing studies have examined the pedestrian safety at an intersection in homogeneous condition using simulation, surrogate safety models, and video analysis technique. Many researchers have evaluated the safety of pedestrian and factors affecting the crossing behaviour of a pedestrian at signalized intersection in heterogeneous condition. Fu et al. presented an automated video-based methodology for safety analysis for pedestrian crossings at an unsignalized intersection having homogeneous traffic conflicts and PET value less than 1.5 seconds as dangerous conflict. They have shown that pedestrians were exposed to higher risk levels at the study sites in the night-time as opposed to daytime conditions. From the literature review, it was found that there has not been as surrogate measure-based methodology available that can examine the pedestrian safety at the unsignalized intersections under mix traffic condition (According to author's knowledge). The preliminary study was conducted using the parameters related to pedestrians. This paper provides the detailed framework to evaluate the pedestrian safety at the unsignalized intersections under mix traffic condition using surrogate safety measures. PET, one of the most 2 commonly used surrogate safety indicators, is chosen to evaluate the pedestrian safety.

1.2 Problem statement

Road safety for pedestrians is a matter of great concern looking at its severity, scale, and impact associated with it. Although the number of people using the motorized vehicle has increased in the recent times yet the number of the people using the non-motorised vehicles and the pedestrians is still very large. In urban areas, pedestrian crossing intersection is more complex since the vehicles have very little time to response. A clear understanding of pedestrian crossing behaviour under mixed traffic conditions is needed for providing the necessary infrastructure for the safety of the pedestrians. In our study, Raipur is the developing city of India where the number of pedestrians is more and possibility of conflicts are very high while crossing an unsignalized intersection, as at unsignalized intersection the risk of uncontrolled vehicle speed leading to the accidents is more while crossing the intersection. Evaluating the pedestrian safety at the unsignalized intersection will lead the improvement of infrastructure for the safe pedestrian crossing. The use of actual accident data, in a developing country like India is also questionable as well as not reliable. So, the use of the surrogate safety measures seems more reliable as we do not have to wait for the actual accident to occur at the site and can be studied at any time. From the surrogate safety measures present for the studies, comparison of the best safety measure will help to obtain the data without actual videographic survey with help of just the speed of the vehicles. Accurate evaluation of the unsignalized intersection will provide the alternate measures to provide the safety of the pedestrians in such intersections. Such measures will help in efficient and safe crossing of pedestrians in an unsignalized intersection.

1.3 Objective

As the pedestrians are one of the most vulnerable road users, the proper measures should be developed to ensure the safety of the pedestrian. So, the objectives of this study are:

1. To propose a surrogate safety based proactive methodology to quantify pedestrian safety at the unsignalized intersection under non-lane based heterogeneous traffic condition by using the proximal safety indicator: Post Encroachment Time (PET).
2. To develop a suitable framework to classify conflicts based on their severity level by providing the threshold PET values for highly severe conflict, severe conflict

and normal conflict considering vehicle-related parameters suitable for non-lane based heterogeneous traffic condition at the unsignalized intersection.

3. To compare various supervised classification machine learning models to obtain maximum accuracy of classification.

1.4 Scope of Study

The study has been done in front of the National Institute of Technology Raipur trisection. The study provides methodology to examine the safety of the pedestrians in an unsignalized intersection for the mixed traffic. The conflict is classified as highly severe, severe, and normal on the basis of the observation of behaviour of the pedestrians and then predicted on the basis of the PET values obtained from the statistical and machine learning model.

After that, test data is analysed by creating the success prediction table based on observed and predicted data using both statistical and machine learning model. Model with greater accuracy is chosen to obtain the threshold PET values.

This analysis is done to obtain the most accurate model and to obtain the behaviour of traffic in intersection only based on PET and speed of vehicle without conducting the actual survey. After comparison of observed and predicted data, traffic conflicts are classified as highly severe, severe, and normal conflict, thus resulting weather the intersection is safe for the pedestrians or not. And if not, then provide the adequate measures so that the use of intersection becomes safe for the users.

Typically, the intersections are designed on the basis of vehicular characteristics but, the intersections also need to ensure pedestrian safety. Different pedestrian facilities are designed on basis of the behaviour of pedestrian as well as the driver but with time development of road takes place which results in the change in road user characteristics and pedestrian volume. Therefore, there is a possibility that we require to upgrade the pedestrian facilities.

Thus, to analyse the severity of current situation we can use this model and provide the standards for the comparison of two similar intersection.

The structure of this study is organized as follows: in the Section 2 we review the existing literature on proactive surrogate safety measure in India using SVM and CDF analysis. Then Section 3 describes data collection from primary and secondary sources and analysis of the collected data. In this section proposed methodology of both the stages is also discussed. In Section 4 result and discussion of both the stages is provided. The report ends with conclusion of the whole study in Section 5.

2 Literature review

In road network, pedestrian safety is commonly analysed in terms of the number of crashes between pedestrian and vehicle (Kocourek, Padělek 2016; Roshandeh et al. 2016). However, this approach failed to quantify actual safety conditions for pedestrians due to unavailability of accident data and exposure measures. Most of the existing studies on pedestrian safety have been examined using historical accident data, depends on frequency and severity. Few studies list the limitations of using accident data for pedestrian safety analysis, such as low-mean sample, underreporting, misallocation, and misclassification (Persaud et al. 2013). Pedestrian safety evaluation at intersections can be evaluated into two major methods: accident rate, and conflict method. Both methods have some limitations such require large data, need secondary data, lesser evaluation in findings, and lesser accuracy level (Wang, Abdel-Aty 2008). To overcome those problems, proactive methods have been introduced which does not require any accident or secondary data and rely on surrogate measures of safety. Surrogate measure techniques observe non-crash event, which is related in a reliable way to actual crashes and convert those non-crash event into the corresponding crash severity level. Surrogate measures provide more better and precise alternative safety indicators and used to identify the various risk factors on before-after control studies (Vedagiri, Killi 2015; Nadimi et al. 2016; Zangenehpour et al. 2016). Most of the existing studies have adopted Traffic Conflicts Technique (TCT) as SSM to quantify the conflict severity level. TCT measures as a conflict, which occur much more frequently than crashes and provide information on relative risk at facilities (Song, Yang 2011; Cafiso et al. 2015; Fu et al. 2016). However, TCT has some limitations when conflict happened between pedestrian and vehicle, because of complex movement dynamics and grouping, non-rigid and less organized nature of pedestrian. Therefore, some existing studies have utilized PET to measure the severity index of conflicts. The PET between two road users can be used as surrogate measures and it is defined as the period from the moment when the first road users leave the conflict area until the second road user reaches it (Ni et al. 2013; Cafiso et al. 2015; Fu et al. 2016; Vedagiri, Killi 2015; Nadimi et al. 2016; Zangenehpour et al. 2016). Intersections have a large impact on the pedestrian–vehicle interaction, which influences the pedestrian safety and severity. PET relates to interaction severity explained the low or unreported model fitness in existing studies. Therefore, there is a need to develop and testing a new safety surrogate measure for pedestrian crosswalk at signalized intersections, particularly in India. The major contribution of this paper is to propose the accurate PET values for pedestrians from the real-world data and improve the accuracy level of the pedestrian PET prediction by proposing a mathematical model under mixed traffic conditions.

Proactive surrogate safety measure is the method of evaluation using the surrogate measures instead of the actual accident data. For the evaluation using surrogate safety we have different parameters like the Post Encroachment Time, vehicle approach speed, gender, age, behaviour of pedestrian, actions taken by the driver as well as the pedestrian at the time of the conflict etc., the following literature review consists of study of various proactive surrogate safety measures such as SVM model and CDF analysis which can be used to evaluate the pedestrian safety at the unsignalized intersection.

A) **Proactive pedestrian safety evaluation at unsignalized intersections in India using surrogate safety measures**

Author: Harsh Shah, Dr. P. Vedagiri (2019)

Surrogate safety measures are based on the idea that accidents evolve from conflicts, which are situations where the probability of a collision is high. There are many of these safety indicators like Post Encroachment Time (PET), Time- to- Conflict (TTC), Deceleration-to-Safety Time (DST), Time-to-Zebra (TTZ) and Time-to-Line Crossing (TLC) which have been used in different studies. Van der Horst (1990) had recorded various conflicts between car-car, car-bicycle, and car-pedestrian at the urban intersection in homogeneous traffic condition and derived the combined cumulative PET distribution for all conflicts.

PET, one of the most common used surrogate safety indicators in the Road Safety analysis, is chosen to evaluate the pedestrian safety. This measure is used to evaluate situations in which two road-users that are on a collision course, pass over a common spatial point or area with a temporal difference that is below a predetermined threshold. (Pirdavani et al. 2010). PET is chosen for this study as it is more suitable for transverse collisions which generally occur between pedestrian and vehicle at uncontrolled intersections.

Few studies have carried out the proactive safety evaluation of an unsignalized intersection for vehicle-vehicle conflict in mix traffic condition. (Deepak and Vedagiri

2014; Shekhar Babu and Vedagiri 2016) Many of the existing studies have examined the pedestrian safety at an intersection in homogeneous condition using simulation, surrogate safety models or video analysis technique. (Agarwal 2011; Olszewski et al. 2016). There are many existing studies also available for evaluation of pedestrian safety and factors affecting the crossing behaviour of a pedestrian at signalised intersection. (Hao et al. 2008; Marisamynathan and Vedagiri 2013). To assess the safety of pedestrians considering conflicts with left-turners Alhajyaseen et al. (2012) have developed a path model, free-flow speed model, lag/gap acceptance model, and stopping/clearing speed profile model based on intersection geometry and characteristics of the pedestrian movement. Few studies have studied the pedestrian safety analysis at a unsignalized intersection in homogeneous traffic condition. Fu et al. (2015) presented an automated video-based methodology for safety analysis for pedestrian crossings at an unsignalized intersection having homogeneous traffic condition during night-time. They have considered PET values less than 5 seconds as conflicts and PET value less than 1.5 seconds as dangerous conflict. They have shown that pedestrians were exposed to higher risk levels at the study sites in the night-time as opposed to daytime conditions.

B) **Pedestrian safety evaluation of signalized intersections using surrogate safety measures**

Authors: Sankaran MARISAMYNATHAN, Perumal VEDAGIRI (2018)

The large proportions of pedestrian fatalities led researchers to make the improvements of pedestrian safety at intersections. Thus, the paper proposed by researchers had a methodology to evaluate crosswalk safety at signalized intersections using Surrogate Safety Measures (SSM) under mixed traffic conditions. The required pedestrian, traffic, and geometric data were extracted based on the videographic survey conducted at signalized intersections in Mumbai (India). Post Encroachment Time (PET) for each pedestrian were segregated into three categories for estimating pedestrian–vehicle interactions and Cumulative Frequency Distribution (CDF) was plotted to calculate the threshold values for each interaction severity level. The Cumulative Logistic Regression (CLR) model was developed to predict the pedestrian mean PET values in the crosswalk at signalized intersections. The proposed model was validated with a new signalized intersection and the results were shown that the proposed PET ranges and model appropriate for Indian mixed traffic conditions.

Summary of Literature Review:

After thorough literature review of relevant research paper published on pedestrian safety evaluation using surrogate safety measures the following techniques can be adopted for the proposed project:

- PET is chosen as surrogate safety indicators in the Road Safety analysis for evaluation of pedestrian safety which is adopted from research paper given by Harsh Shah and P. Vedagiri.
- Conflict is classified in various classes based on their severity level on the basis of behaviour of pedestrian-vehicle as highly severe, severe, and normal is adopted from research paper given by Harsh Shah and P. Vedagiri.
  In this paper, conflict is classified as Highly sever if in the conflict vehicle stops or pedestrian speeds up to avoid the conflict. Similarly, conflict is classified as Severe if vehicle or pedestrian slow down their speed, and Normal conflict if there is no interaction between pedestrian and vehicle.
- Cumulative Frequency Distribution (CDF) analysis for segregation into three categories is adopted from the research paper given by Sankaran Marisamynathan, Perumal Vedagiri.
- The threshold PET values of each conflict group were obtained using Support Vector Machine algorithm adopted from the research paper given by Harsh Shah and P. Vedagiri.

3 Data collection and analysis

3.1 Study area

Raipur is the capital of one of the newly established Indian states, situated in the fertile plains of Chhattisgarh. Traditionally, Raipur's economy has been based on Steel, Cement, Alloy, Agricultural-processing, Forest Produce and Rice. Located centrally in the state of Chhattisgarh, the city now serves as a regional hub for trade and commerce for a variety of local agricultural and forest products as well. The industries in coal, power, steel, and aluminium etc. have a spill-over impact in the entire Raipur Urban Agglomeration region and so a string of commercial and industrial development is taking place in the fringes of development area. Raipur is largest market of Steel in India. Raipur is among the richest cities and India's biggest iron market; there are about 200 steel rolling mills, 195 sponge iron plants, more than 20 large scale steel plants, more than 60

Plywood Factories 500 agro-industries and more than 35 Ferroalloy plants. There are more than 800 rice milling plants, and all major and local cement manufacturing companies (Century Cement, Ambuja, Grasim, Lafarge) have a presence in the city. The map of city is shown in Figure 1.

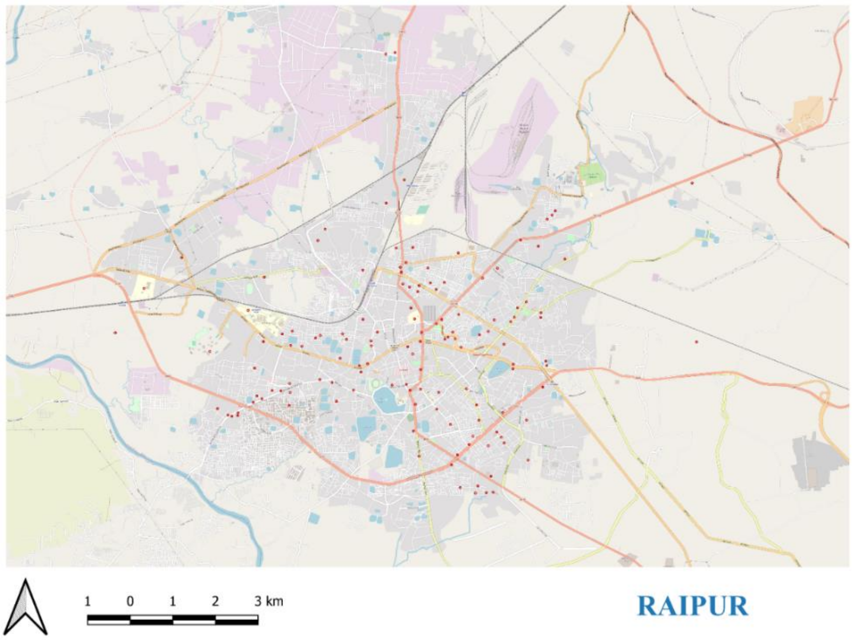

Figure 1: Map of Raipur city, Chhattisgarh

3.2 Analysis of Data

In road network, pedestrian safety is commonly analysed in terms of the number of crashes between pedestrian and vehicle. But this approach failed to quantify what are the actual safety conditions for pedestrians due to unavailability of accident data and exposure measures. Most of the existing studies on pedestrian safety have been examined using historical accident data, depends on frequency and severity. Pedestrian safety evaluation at intersections can be assessed using two major methods: accident rate, and conflict method. But the limitations of both the method is that it requires large data, need secondary data, lesser evaluation in findings, and lesser accuracy level. To overcome those problems, proactive methods have been introduced which does not require any accident or secondary data and rely on surrogate measures of safety. Surrogate measure techniques help to observe non-crash event, which is related in a reliable way to actual crashes and convert those non-crash event into the corresponding crash severity level. Surrogate measures provide more better and precise alternative safety indicators and used to identify the various risk factors on before-after control studies. In this project PET is considered as the surrogate safety measure.

PET may be defined as time from the moment a road user leaves the conflict area to the second road user reaching it. Intersections have a large impact on the pedestrian vehicle interaction, which influences the pedestrian safety and severity. The major contribution of this paper is to propose the accurate PET values for pedestrians from the real-world data and improve the accuracy level of the pedestrian PET prediction by proposing a mathematical model under mixed traffic conditions.

3.2.1 Definition of Post Encroachment Time (PET)

For the proactive road safety analysis, PET is one of the most used surrogate safety measures. In this study, PET is chosen as a safety indicator in this study due to its suitability for the transverse conflicts. PET is used to evaluate the conflict in which two road users are on collision path and with a temporal difference they pass over a common spatial point or area. So, PET is defined as a difference between time notes Tl and T2, where Tl is defined as a time moment at which the first road user (Vehicle/ Pedestrian) leaves the conflict area and T2 is defined as a time moment at which second road user enters the conflict area. The smaller PET value implies, the greater proximity of collision, and if both the road users are in the conflict area, then the PET value will be less than zero, which shows the accidental or near miss condition. In this study, PET is extracted using suitable grid method.

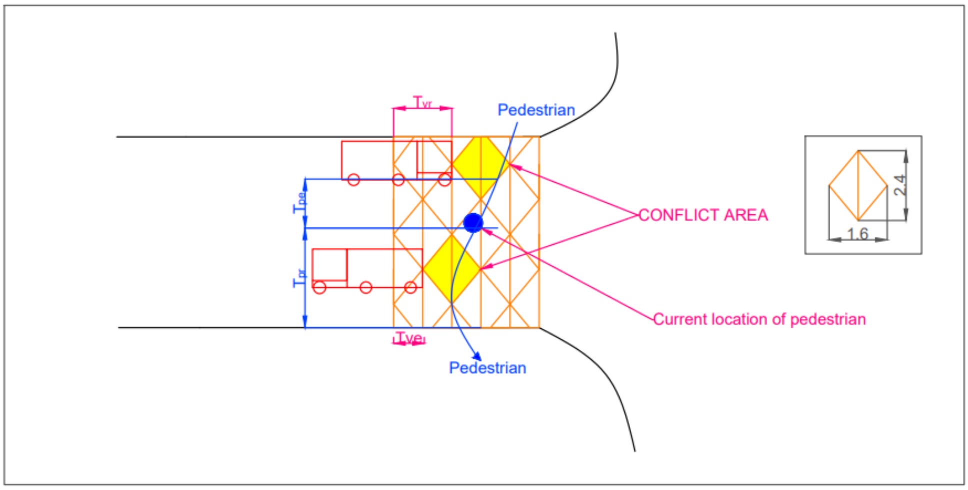

Figure 2: Diagrammatic representation of grids

where,

T_{vr}	time of vehicle reach in a particular rhombus
T_{ve}	time of vehicle exit from a particular rhombus
T_{pr}	time of pedestrian reach in a particular rhombus
T_{pe}:	time of pedestrian exit from a particular rhombus

So, as per notation defined in Figure 2, PET calculation can be generalized as: In the situation where the pedestrian reaches the conflict area before the vehicle, the relation between T_{vr} and T_{pe} will be $T_{vr} > T_{pe}$, so PET is a time difference of T_{vr} and T_{pe}. In the situations where the vehicle reaches at the conflict area before the pedestrian, the relation between T_{pr} and T_{ve} will be $T_{pr} > T_{ve}$ so, in this case, PET is a time difference of T_{pr} and T_{ve}.

$$PET = \begin{cases} |Tvr - Tpe|, \text{when pedestrian reaches the conflict area before the vehicle} \\ |Tpr - Tve|, \text{when vehicle reaches at the conflict area before the pedestrian} \end{cases}$$

3.2.2 Data collection and extraction

The intersection under study is typical three arm urban unsignalized intersection located in, Raipur (Figure 3). The data was collected in the form of video tapings for off-peak hours. Both major and minor road have effective two lanes for the vehicle movement. The crosswalk marking was not available at the time of the survey. Considering the elliptical influence area of a pedestrian having a minor axis and major axis 0.45 m (l .48 ft.) and 0.6 m (1.97 ft.) respectively, the shape of the grid was adopted. However, this size of the shape is minuscule to accommodate the normal size of the vehicle, and elliptical shape has its own complexities. So, instead of elliptical shape, rhombus shape grid was selected having appropriate size (i.e., 1.6 m x 2.4 m (5.25 ft. x 7.87 ft.)) as shown in Figure 2. The final size of rhombus shape was adopted based on the field observation and the trial of different sizes of a rhombus shape. The straight lines are provided in the grid network, were used to ease the data extraction work. These straight lines were used instead of the transverse boundary of rhombus to get entry time and exit time of the straight moving vehicles from the conflict area. For left turning vehicles, the transverse line of a rhombus is used. The straight lines away from the grid network were used to extract the approaching speed of the vehicle. The grids have been drawn manually in AutoCAD 2023 software. Then the image of the grid exported and converted into a transparent picture, for overlaying it on the video. The grid is then overlaid on the video using Corel Video Studio ProX9 software. The conflicts were extracted manually from videos using VLC media player.

Figure 3: Location of study area with the grid

During data extraction, Post Encroachment Time (PET) was extracted to evaluate the severity of that conflict. In addition to that, various other vehicle parameters like an average vehicle approaching speed, type of the vehicle and behaviour of road users (Vehicle & Pedestrian) during the conflict were extracted.

3.2.3 Severity classification of Pedestrian—Vehicle Conflict

The conflicts between Vehicle and Pedestrian were classified into three groups as per their behaviours during the conflict. These 3 levels of conflict are as follows:

1. **Highly Severe conflict:** The conflict is considered as highly severe conflict when one of the two (mostly pedestrian) or both road users stop to avoid the conflict, or the pedestrian increases their speed to avoid the accident. This represents the highest probability of an accident. E.g., Near miss accident.
2. **Severe Conflict:** The conflict is considered as severe conflict one of the two or both road user decreases their speed or change their path to avoid an accident. This represents the moderate probability of an accident.
3. **Normal conflict:** the conflict is considered as normal conflict when both road users move at their normal speed (i.e., comfortably passing conflict zone.) So, they have very less chance of an accident i.e., no interaction between vehicle and passenger.

According to this classification, all vehicle-pedestrian conflicts were grouped into three groups for all type of vehicle type. For that during the data extraction, the behaviour of road user was observed to decide the severity of the conflict.

3.3 Analysis models

3.3.1 Cumulative Distribution Frequency (CDF) Model

A variable that represents the outcome of a trail, an event or an experiment is termed as random variable. Determination of probability of this random variable, we use a Cumulative distribution Frequency (CDF) analysis. It can be defined as the probability that random variable is not greater than a specific value. CDF of a distribution function X, evaluated at any point x, is the probability that X will take a value less than or equal to x (Equation 1). CDF may be defined for both random variables and discrete variables and is used to specify distribution of multivariate random variables. CDF data can be easily plotted on excel sheet with the probability distribution of random variables.

The CDF defined for a discrete random variable and is given as,

$$F_x(x) = P(X \leq x) \tag{1}$$

Where X is the probability that takes a value less than or equal to x and that lies in the semi-closed interval (a,b], where a < b.

Therefore, the probability within the interval is written as,

$$P(a < X \leq b) = F_x(b) - F_x(a) \tag{2}$$

The CDF defined for a continuous random variable is given as,

$$\mathrm{Fx}(x) = \int_{-\infty}^{x} \mathrm{fX}(t)\,dt \tag{3}$$

Here, X is expressed in terms of integration of its probability density function $f_{x.}$

Cumulative Distribution Function is used in statistical analysis in two ways.

- Frequency of occurrence of values for the given phenomena is obtained using cumulative frequency analysis.
- To derive some simple statistics properties, by using an empirical distribution function, that uses a formal direct estimate of CDF.

3.3.2 Support Vector Machine (SVM) Model

Support-Vector Machine (SVM) is one of supervised machine learning algorithm which analyse data for classification and regression analysis. SVM can solve both linear and non-linear problems. This algorithm creates a hyperplane in N-dimensional space which separates the data points into classes. The goal of SVM model is to make a decision boundary in a way such that separation between two features/classes is as wide as possible. A hyperplane is placed dividing the classes in a way that there is a maximum distance between hyperplane and margins. Margin is a plane parallel to hyperplane placed on both sides and passing through the support vectors, in such a way that the distance is maximised. This model does not require assumption about the distribution of data being analysed.

Different SVM Kernels are used to classify non-linear data by projecting the non-linear data into higher dimension space. Here, Kernels are the set of mathematical functions which take data as input and transform them in required form. Different types of kernel functions are linear, non-linear, polynomial, radial basis function (RBF), and sigmoid.

Gamma is hyperparameter which defines how far the influence or curvature we want in a decision boundary. If we take low value of gamma, that means for choosing right hyperplane we calculate gap between every data point with the line, and if we take high value of gamma, we check gap between the closest data points with the line. Gamma is used for Gaussian RBF Kernel only.

C hyperparameter or the regularization parameter controls error while choosing the right hyperplane. It means adding some value in the error function to improve the result. We use C term to tell SVM algorithm how much mis-classification to avoid. Low regularization value means some mis-classification error i.e., the model is more tolerant of errors. High regularization value gives more accurate classification.

For classifying linearly separable data, the discriminant function related with hyperplane is,

$$F(x) = w^T.x + b \tag{4}$$

where, $w^T.x$ represents a dot product, w is neuron weight vector and b is bias/offset.

If we have linearly separable training dataset, then two hyperplanes can be selected in a way such that there in no data point in between. This region between hyperplanes is termed as margin. If it isn’t possible to get hyperplanes which separates the datasets cleanly, we find error tolerant margin also termed as soft margin which is given by 2/||w||. Therefore, to maximize the gap between boundary ||w|| must be minimum. Hence optimization problem is given by,

$$\min_{w,b,\xi}\{\frac{||w||^2}{2} + C\sum_{i=0}^{n}\xi_i\} \tag{5}$$

$$y_i(w^T.x_i + b) \geq 1 - \xi_i \tag{6}$$

For non-separable dataset, slack variables ξ_i and c are required but for linearly separable dataset, their value is zero. Cover’s theorem is used to switch linear problem to nonlinear boundary problem which states that "input data, which are linearly non separable into input space I (under certain assumptions) can be mapped to another space F (called feature space), in which data can be linearly separable". A kernel function is used to transform the data into high dimensional space and construct the optimal hyperplane for different types of non-linear data. The maximum margin hyperplane can be represented regarding support vector is,

$$\sum_{i \epsilon n} \alpha_i y_i k(x_i, x_j) + b \tag{7}$$

Where α_i = Lagrange multipliers, n = set of support vector, in this study Gaussian Linear kernel is used i.e.,

$$k(x_i, x_j) = x_i * x_j \tag{8}$$

Flow chart of SVM model is shown in Figure 4.

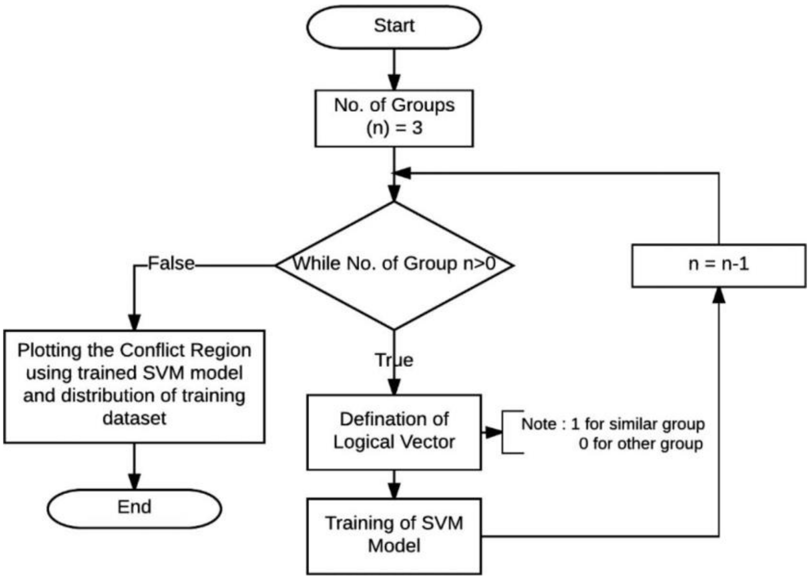

Figure 4: Flow chart for SVM model [Source: Harsh Shah, Dr.P. Vedagiri, 2017]

4 Data explanation and analysis

4.1 Data explanation

For this study area 166 data were extracted from 2.5 hrs video using VLC media player and stopwatch. For the extraction of PET values rhombus grid of dimension 2.4*1.6 m is used. In the situation where the pedestrian reaches the conflict area before the vehicle, the relation between T_{pe} and T_{vr} will be $T_{vr} > T_{pe}$, so PET is a time difference of T_{vr} and T_{pe}. In the situations where the vehicle reaches at the conflict area before the pedestrian, the relation between T_{pr} and T_{ve} will be $T_{pr} > T_{ve}$ so, in this case, PET is a time difference of T_{pr} and T_{ve}.

For each case vehicle speed is calculated for marked 30 m distance using stopwatch. Also, various factors like gender, age, vehicle type and reaction of pedestrian to the conflict (pedestrian stop, pedestrian speed up, vehicle slow down, pedestrian slow down, no interaction) is noted.

Classification of various levels of conflict based on observed behaviour of pedestrian is done as,

No interaction	Normal conflict
Vehicle or Pedestrian slow down	Severe conflict
Vehicle Stop + Pedestrian speed up	Highly Severe conflict

Now CDF and SVM analysis is done and based on these observed behaviour success prediction table for both analysis is resulted.

4.2.1 Cumulative Distribution Frequency (CDF) Analysis

Cumulative Distribution Frequency analysis is carried out in MS Excel with 80% of the data to prepare a CDF plot between Frequency Percentile and Post Encroachment Time (PET). The PET value of 15 percentile and 50 percentile is considered for classification. Therefore, for the PET value less than 15 percentile will be classified as highly severe, between 15 to 50 percentiles will be considered as severe and PET values more than 50 percentile will be considered as normal.

$$\text{for PET} = \begin{cases} < 15 \text{ percentile, Highly severe conflict} \\ 15 - 50 \text{ percentile, Severe conflict} \\ > 50 \text{ percentile, Normal conflict} \end{cases}$$

For preparing a CDF plot, a range of 0 to 0.5 is considered and frequency of PET is according to range is counted as shown in Table 1.

Table 1: CDF calculation table

PET Range		Upper limit	Frequency	Cumulative	Percentage (%)
0	0.5	0.5	0	0	0
0.5	1	1	14	14	10.61
1	1.5	1.5	42	56	42.42
1.5	2	2	31	87	65.91
2	2.5	2.5	15	102	77.27
2.5	3	3	8	110	83.33
3	3.5	3.5	12	122	92.42
3.5	4	4	3	125	94.7
4	4.5	4.5	2	127	96.21
4.5	5	5	2	129	97.73
5	5.5	5.5	1	130	98.48
5.5	6	6	1	131	99.24
6	6.5	6.5	1	132	100
6.5	7	7	0	132	100
7	7.5	7.5	0	132	100
7.5	8	8	0	132	100

A graph is plotted between the Upper limit of PET range and Percentage as shown in Figure 5. PET value of 15 percentile and 50 percentile is calculated from the graph. The PET value of 15 percentile is 1.06 seconds and 50 percentile 1.71 seconds. Thus, the PET values which are less than 1.06 seconds is classified as Highly severe, PET values between 1.06 seconds and 1.71 seconds are classified as Severe and PET values greater than 1.71 seconds is classified as Normal conflict.

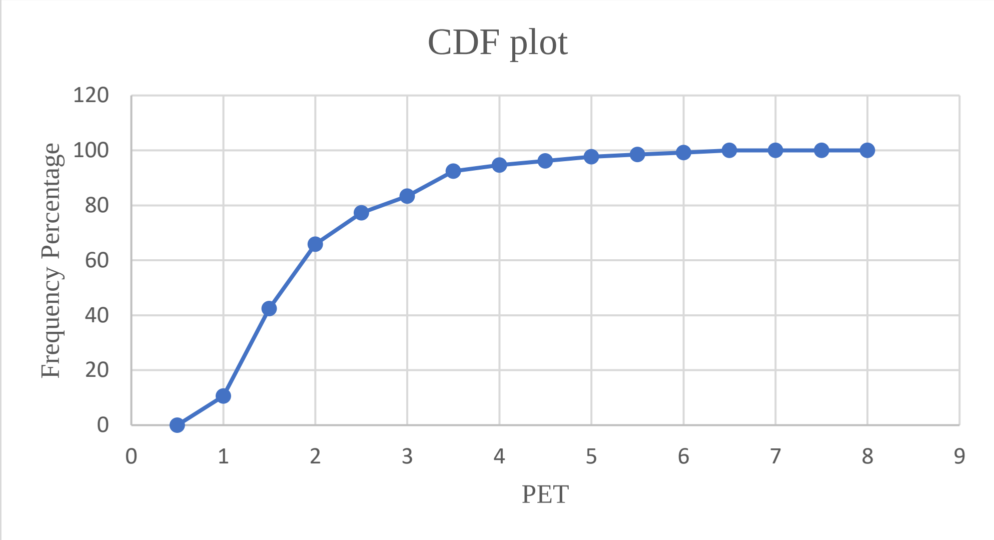

Figure 5: CDF Plot – PET vs Frequency percentage

Now rest 20% data is tested and classified according to obtained PET values and Success Prediction table is created based on observed and predicted classification (Table 2).

Table 2 Success Prediction Table (CDF)

Observed	Predicted			Row Total	Observed Share
	Highly Severe	Severe	Normal		
Highly Severe	8	7	3	18	52.94%
Severe	2	3	0	5	14.70%
Normal	0	0	11	11	32.36%
Column Total	10	10	14	34	100.00%
Predicted Share (%)	29.41%	29.41%	41.18%	**Overall Success**	**64.70%**
% Correctly Predicted	44.44%	60.00%	100.00%		

This model gives overall success of 64.7% with only input parameter as PET.

4.2.2 Support Vector Machine (SVM) Analysis

For SVM analysis, dataset is prepared using Vehicle speed, PET, and Class variables in the csv format. Here Class contains values 0,1, and 2 depicting highly severe, severe, and normal conflict based on observations.

SVM analysis is carried out in Jupyter Notebook using Python. This model is trained using 80% of the data and tested with remaining 20% of the data. Finally, Success prediction table is prepared based on Confusion matrix obtained using SVM analysis.

Code:

```
>>> import pandas as pd
    import numpy as np
    from sklearn.model_selection import train_test_split
    from sklearn import svm, datasets
    from sklearn.svm import SVC
    from sklearn.metrics import classification_report
    from sklearn.metrics import accuracy_score
    from mlxtend.plotting import plot_decision_regions
    from sklearn.metrics import confusion_matrix
```

```
>>> cell_df = pd.read_csv('Speed-PET.csv')
    cell_df.head()
```

	PET	Speed	Class
0	0.90	41	0
1	0.56	37	0
2	0.62	31	0
3	0.63	33	0
4	0.68	39	0

```
>>> feature_df = cell_df[['PET', 'Speed ']]
    X = np.asarray(feature_df)
    y = np.asarray(cell_df['Class'])
```

```
>>> X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=4)
```

```
>>> classifier = svm.SVC(kernel='linear', gamma='auto', C=3)
    classifier.fit(X_train, y_train)
    y_predict = classifier.predict(X_test)
    print(classification_report(y_test, y_predict))
    print("Accuracy Score:",accuracy_score(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       0.67      0.67      0.67        12
           1       0.67      0.67      0.67         9
           2       0.92      0.92      0.92        13

    accuracy                           0.76        34
   macro avg       0.75      0.75      0.75        34
weighted avg       0.76      0.76      0.76        34

Accuracy Score: 0.7647058823529411
```

```
>>> cmatrix = confusion_matrix(y_predict, y_test)
    print(cmatrix)
```

```
[[ 8  3  1]
 [ 3  6  0]
 [ 1  0 12]]
```

```
>>> plot_decision_regions(y= y_train,
                          X= X_train,
                          clf=classifier,
                          legend=1,
                          colors=('red,pink,yellow,blue,green,cyan')
                          )
```

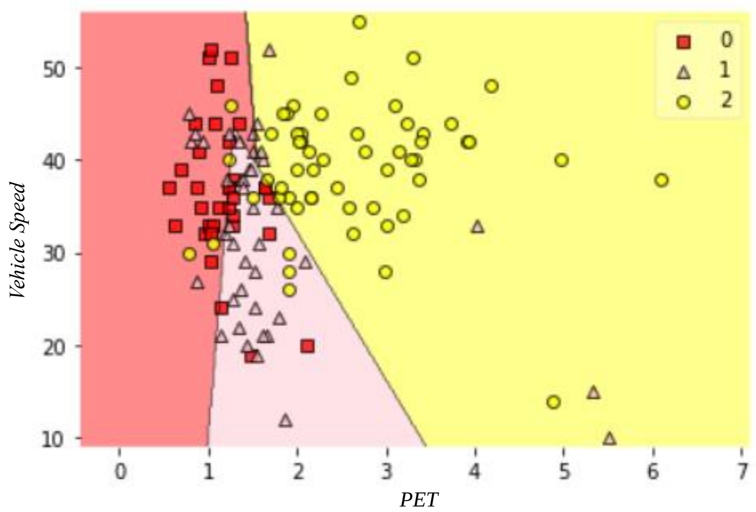

Figure 6 Training Data set

```
>>> plot_decision_regions(y= y_test,
                          X= X_test,
                          clf=classifier,
                          legend=4,
```

colors=('red,pink,yellow,blue,green,cyan')

)

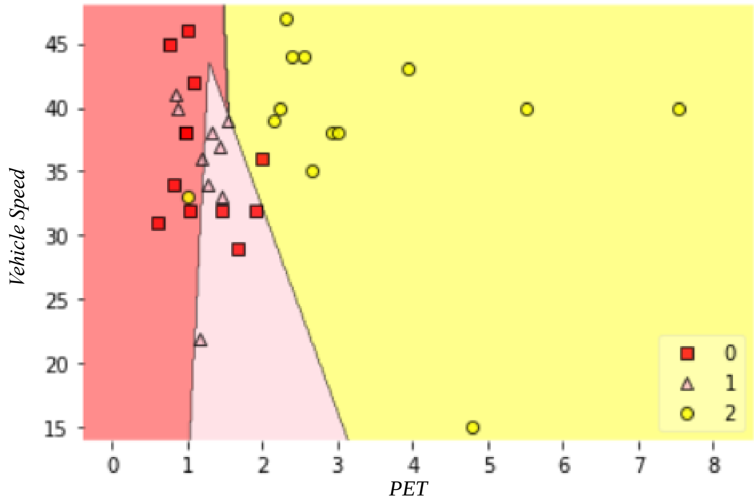

Figure 7 Test Data set

>>> plot_decision_regions(y= y_predict,

X= X_test,

clf=classifier,

legend=4,

colors=('red,pink,yellow,blue,green,cyan')

)

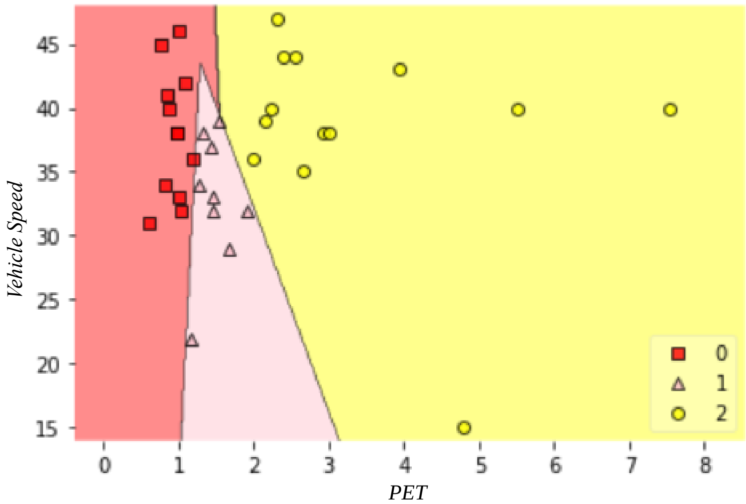

Figure 8 Predicted Dataset graph

In the analysis, Linear kernel was considered with regularization value of 3 as for other kernels i.e., rbf, poly, sigmoid the accuracy score was less than that of linear kernel (0.7647). Accuracy score of rbf kernel was 0.588 and that of poly kernel with degree 6 was 0.6470. Thus, Linear kernel with cost(C) value 3 proved to be more accurate than others. According to Figure 7 and Figure 8 graph obtained by SVM, if PET is less than 1 seconds and vehicle speed is greater than 30 Kmph then conflict is classified as highly severe conflict, if the vehicle speed is greater than 30 Kmph and PET value is greater than 2 seconds OR if PET is greater than 3 seconds then conflict is classified as normal conflict, else severe conflict. We observe that some of the observed data of certain class is predicted as a different class from SVM analysis. Thus, to summarise such kind of result we have formed Success Prediction table, as shown in Table 3, which can easily show such kind of variation.

Table 3 Success Prediction Table (SVM)

Observed	**Predicted**			**Row Total**	**Observed Share**
	Highly Severe	**Severe**	**Normal**		
Highly Severe	8	3	1	12	35.29%
Severe	3	6	0	9	26.47%
Normal	1	0	12	13	38.24%
Column Total	12	9	13	34	100.00%
Predicted Share (%)	35.29%	26.47%	38.24%	**Overall Success**	**76.47%**
% Correctly Predicted	66.67%	66.67%	92.30%		

The SVM model results were compared with other Supervised Machine Learning models like Decision Tree classifier, Random Forest classifier, Gradient Boosting classifier, Naïve Bayes classifier, K-Nearest Neighbors (KNN) classifier and Logistic Regression for the same training and test datasets and the results obtained are as follows:

```
Accuracy Score
____________________________________
Random Forest Prediction: 0.618
Naive Bayes: 0.588
Decision Tree Prediction: 0.676
Gradient Boosting Prediction: 0.676
KNearest Neighbors Prediction: 0.588
Logistic Regression: 0.706
Support Vector Machine: 0.765
____________________________________
```

This indicates that Support Vector Machine model gives highest accuracy score and thus a best model to use in this scenario.

Both CDF and SVM analysis were performed using same values of 80% and 20% dataset but with 1 input parameter (PET) and 2 input parameters (PET and Vehicle Speed) respectively. Thus, giving an overall success prediction of 64.7% for CDF and 76.47% for SVM.

5 Result and Discussion

This study carried out evaluation of pedestrian safety in an un-signalised intersection using an effective proactive surrogate safety indicator i.e., Post Encroachment Time (PET). To classify the conflicts between pedestrian and vehicles as highly severe, severe, and normal conflicts, PET and vehicle speed were used as the parameters. Two different models Cumulative Distribution Frequency (CDF) and Support Vector Machine (SVM) are developed to obtain the threshold PET values. In CDF, to classify various classes of conflicts 15 and 50 percentile PET values from CDF plot were considered. Thus, PET value between 0-1.06 seconds, 1.06-1.71 seconds, and greater than 1.71 seconds indicates highly severe, severe, and normal conflicts respectively. According to Figure7 and Figure 8, graph obtained by SVM, if PET is less than 1 seconds and vehicle speed is greater than 30 Kmph then conflict is classified as highly severe conflict, if the vehicle speed is greater than 30 Kmph and PET value is greater than 2 seconds OR if PET is greater than 3 seconds then conflict is classified as normal conflict, else severe conflict. For both the models the accuracy score according to Success-Prediction table for same training and test data set are 64.7 % (CDF) and 76.47% (SVM). This difference may be due to input parameters considered in both the models i.e., PET and vehicle speed in SVM and only PET in CDF. This implies vehicle speed plays a significant role on threshold PET values. This suggests that supervised machine learning SVM model predicts more accurately than Cumulative Distribution Frequency (CDF) model.

6 Conclusion

This study is carried out in Raipur city, Chhattisgarh. It proposed methodology to carry out the safety assessment without putting pedestrians at risk in the interim. The accuracy and reliability of the available pedestrian-vehicle accident data are highly questionable as no standard data recording method is followed. So, more effective, and proactive safety evaluation technique is necessary for the evaluation. Thus, we proposed a proactive safety evaluation methodology at an unsignalized intersection as it includes the conflict which is more frequent than the actual happening of the accidents by which we can evaluate safety of intersection without waiting for actual accident to happen and thus is more effective, significant, and reliable measure of traffic safety. In the study, we proposed the PET as a proximal surrogate safety indicator. Using these PET values, we classify the conflicts as Highly severe conflict, Severe conflict, and Normal conflict. For PET value extraction, conflict area is considered in the form of rhombus. A grid is formed considering rhombus shaped influence area and is placed in the direction of pedestrian movement where probability of conflicts was high. Two models CDF and SVM were proposed and resulted threshold PET's according to vehicle speed and PET as parameters. Overall, the accuracy of SVM model resulted was more than CDF model. The study shows that, if PET value for vehicle-pedestrian conflict is more than 3 seconds then both participants are crossing the conflict zone comfortably. Though this study is limited for only one intersection, these threshold values can also be useful to check and compare the pedestrian safety at other unsignalized urban intersections. This will also help to identify the most dangerous unsignalized intersection regarding pedestrian safety by just measuring the PET values for pedestrian-vehicle conflict. These numerical threshold values can be used to develop a real-time application like traffic management system and advance safety warning system. These advanced systems will help both driver and pedestrian to cross the conflict area comfortably.

7 References

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Annexure 1

Pedestrian				Vehicle			Remark	wheeler	PET
Reach	Exit	Gender	Age	Reach	Exit	Speed			
0.78		F	young		0	30	no interaction	2	0.78
1.26		F	young		0	46	no interaction	2	1.26
1.66		F	young		0	38	no interaction	4	1.66
2.05		F	young		0	42	no interaction	2	2.05
2.15		F	young		0	39	no interaction	2	2.15
2.24		F	young		0	40	no interaction	2	2.24
2.3		F	young		0	40	no interaction	2	2.3
3.93		M	young		0	43	no interaction	2	3.93
3.94		M	young		0	42	no interaction	2	3.94
4.19		F	young		0	48	no interaction	2	4.19
	0	M	young	1		33	no interaction	2	1
	0	M	young	1.04		31	no interaction	2	1.04
	0	F	young	1.91		26	no interaction	2	1.91
	0	F	young	4.87		14	no interaction	2	4.87
	0	F	young	2.69		55	no interaction	4	2.69
	0	F	young	3.92		42	no interaction	2	3.92
	0	F	young	2.56		44	no interaction	3	2.56
	0	M	young	3		38	no interaction	4	3
	0	F	young	1.94		46	no interaction	2	1.94
	0	F	young	2.4		44	no interaction	2	2.4
	0	M	young	7.54		40	no interaction	2	7.54
	0	M	young	6.1		38	no interaction	2	6.1
	0	F	young	3.31		51	no interaction	4	3.31
	0	M	young	2.61		49	no interaction	4	2.61
	0	F	old	3		39	no interaction	2	3
	0	F	old	4.97		40	no interaction	2	4.97
	0	M	young	3.28		40	no interaction	2	3.28
	0	M	young	3.42		43	no interaction	4	3.42
	0	M	young	3.1		46	no interaction	4	3.1
	0	F	young	3.24		44	no interaction	4	3.24
	0	F	young	3.37		38	no interaction	2	3.37
	0	M	young	3.33		40	no interaction	2	3.33
	0	M	young	3.74		44	no interaction	2	3.74
	0	M	young	2.32		47	no interaction	2	2.32
	0	M	young	4.78		15	no interaction	4	4.78
	0	M	young	2.58		35	no interaction	2	2.58
	0	F	old	1.5		36	no interaction	2	1.5
	0	M	old	2.26		45	no interaction	4	2.26
	0	F	old	5.51		40	no interaction	2	5.51
	0	M	young	2.67		43	no interaction	3	2.67
	0	F	young	2.66		35	no interaction	2	2.66
	0	F	young	3.4		42	no interaction	2	3.4
	0	F	young	2.45		37	no interaction	2	2.45
	0	F	young	3.14		41	no interaction	2	3.14
	0	M	young	2.18		39	no interaction	2	2.18
	0	F	young	2.15		36	no interaction	2	2.15
	0	M	young	1.8		36	no interaction	2	1.8
	0	M	young	1.23		40	no interaction	2	1.23
1.34		F	young		0	44	pedestrain slowdown	4	1.34
	0	F	young	1.99		36	pedestrian speed up	2	1.99
	0	M	young	1.69		32	pedestrian speed up	2	1.69
	0	M	young	1.28		34	pedestrian speed up	2	1.28
	0	M	young	1.91		32	pedestrian speed up	2	1.91
	0	M	young	2.12		20	pedestrian speed up	2	2.12
	0	F	young	1.08		42	pedestrian speed up	4	1.08
	0	M	young	1.04		32	pedestrian speed up	4	1.04
	0	F	young	0.9		41	pedestrian speed up	4	0.9
0.79		F	young		0	45	pedestrain slowdown	4	0.79

0.8		F	young		0	42	pedestrain slowdown	2	0.8
0.84		F	young		0	43	pedestrain slowdown	4	0.84
0.86		F	young		0	41	pedestrain slowdown	4	0.86
0.87		F	young		0	40	pedestrain slowdown	4	0.87
0.93		F	young		0	42	pedestrain slowdown	4	0.93
1.18		F	young		0	32	pedestrain slowdown	2	1.18
1.2		F	young		0	38	pedestrain slowdown	2	1.2
1.2		F	young		0	36	pedestrain slowdown	2	1.2
1.23		F	young		0	43	pedestrain slowdown	4	1.23
1.24		F	young		0	33	pedestrain slowdown	2	1.24
1.28		M	young		0	34	pedestrain slowdown	4	1.28
1.28		F	young		0	31	pedestrain slowdown	4	1.28
1.49		F	young		0	41	pedestrain slowdown	4	1.49
1.57		F	young		0	31	pedestrain slowdown	4	1.57
1.69		M	old		0	52	pedestrain slowdown	2	1.69
1.77		M	old		0	35	pedestrain slowdown	2	1.77
2.09		F	young		0	29	pedestrain slowdown	2	2.09
4.03		M	old		0	33	pedestrain slowdown	2	4.03
1.45		F	young		0	32	pedestrian speed up	2	1.45
0.56		F	young		0	37	pedestrian stop	2	0.56
0.62		F	young		0	31	pedestrian stop	2	0.62
0.63		F	young		0	33	pedestrian stop	4	0.63
0.68		M	young		0	39	pedestrian stop	2	0.68
0.77		F	young		0	45	pedestrian stop	4	0.77
0.8		M	young	0.87	0	36	pedestrian stop	2	1.67
0.82		M	young		0	34	pedestrian stop	4	0.82
0.84		M	young		0	44	pedestrian stop	4	0.84
0.88		F	young		0	37	pedestrian stop	3	0.88
0.92		M	young		0	35	pedestrian stop	2	0.92
0.97		M	young		0	38	pedestrian stop	4	0.97
0.99		M	young		0	38	pedestrian stop	2	0.99
1		F	young		0	33	pedestrian stop	4	1
1		M	young		0	46	pedestrian stop	4	1
1		M	young		0	51	pedestrian stop	4	1
1.02		M	young		0	29	pedestrian stop	2	1.02
1.03		F	young		0	32	pedestrian stop	4	1.03
1.03		F	young		0	52	pedestrian stop	4	1.03
1.06		F	old		0	33	pedestrian stop	2	1.06
1.08		M	young		0	44	pedestrian stop	2	1.08
1.09		F	young		0	48	pedestrian stop	4	1.09
1.11		F	young		0	35	pedestrian stop	2	1.11
1.14		M	young		0	24	pedestrian stop	4	1.14
1.22		F	young		0	37	pedestrian stop	4	1.22
1.24		F	young		0	35	pedestrian stop	2	1.24
1.24		M	young		0	42	pedestrian stop	4	1.24
1.24		F	old		0	37	pedestrian stop	2	1.24
1.25		F	young		0	51	pedestrian stop	4	1.25
1.27		M	young		0	33	pedestrian stop	3	1.27
1.27		F	young		0	38	pedestrian stop	3	1.27
1.27		M	young		0	36	pedestrian stop	2	1.27
1.32		M	young		0	38	pedestrian stop	4	1.32
1.34		F	young		0	42	pedestrian stop	2	1.34
1.36		M	young		0	26	pedestrian stop	4	1.36
1.37		M	young		0	38	pedestrian stop	3	1.37
1.38		M	young		0	38	pedestrian stop	4	1.38
1.38		F	young		0	37	pedestrian stop	4	1.38
1.43		F	young		0	37	pedestrian stop	2	1.43
1.46		M	young		0	39	pedestrian stop	2	1.46
1.46		M	young		0	33	pedestrian stop	2	1.46
1.47		M	young		0	39	pedestrian stop	3	1.47

1.5		F	young		0	35	pedestrian stop	4	1.5
1.5		M	young		0	43	pedestrian stop	4	1.5
1.53		M	young		0	28	pedestrian stop	2	1.53
1.54		M	young		0	44	pedestrian stop	4	1.54
1.54		F	young		0	39	pedestrian stop	4	1.54
1.59		F	young		0	41	pedestrian stop	2	1.59
1.61		M	young		0	40	pedestrian stop	4	1.61
1.63		F	young		0	37	pedestrian stop	2	1.63
1.63		F	young		0	37	pedestrian stop	2	1.63
1.68		M	young		0	29	pedestrian stop	2	1.68
1.71		M	young		0	43	pedestrian stop	4	1.71
1.81		M	young		0	37	pedestrian stop	3	1.81
1.84		M	old		0	45	pedestrian stop	4	1.84
1.89		M	young		0	45	pedestrian stop	2	1.89
1.9		F	young		0	30	pedestrian stop	2	1.9
1.9		F	young		0	28	pedestrian stop	2	1.9
1.91		M	young		0	36	pedestrian stop	2	1.91
2		F	young		0	35	pedestrian stop	4	2
2		F	young		0	39	pedestrian stop	2	2
2		F	young		0	43	pedestrian stop	4	2
2.02		F	young		0	42	pedestrian stop	2	2.02
2.04		M	young		0	43	pedestrian stop	2	2.04
2.14		F	young		0	41	pedestrian stop	4	2.14
2.63		F	young		0	32	pedestrian stop	2	2.63
2.77		F	young		0	41	pedestrian stop	4	2.77
2.86		M	old		0	35	pedestrian stop	2	2.86
2.93		F	young		0	38	pedestrian stop	3	2.93
2.98		M	old		0	28	pedestrian stop	2	2.98
3.02		F	young		0	33	pedestrian stop	2	3.02
	0	F	young	0.96		32	pedestrian stop	2	0.96
	0	F	young	3.2		34	pedestrian stop	2	3.2
	0	F	young	2.15		36	pedestrian stop	2	2.15
	0	M	young	1.47		19	pedestrian stop	4	1.47
1.28		F	young		0	25	vehicle slow	2	1.28
	0	F	young	0.88		27	vehicle slow	2	0.88
	0	F	young	1.16		22	vehicle slow	4	1.16
	0	M	young	1.87		12	vehicle slow	2	1.87
	0	M	young	5.5		10	vehicle slow	4	5.5
	0	F	young	5.33		15	vehicle slow	4	5.33
	0	F	young	1.8		23	vehicle slow	2	1.8
	0	M	young	1.54		19	vehicle slow	2	1.54
	0	M	young	1.35		22	vehicle slow	2	1.35
	0	M	young	1.53		24	vehicle slow	2	1.53
	0	M	young	1.42		29	vehicle slow	4	1.42
	0	M	young	1.62		21	vehicle slow	2	1.62
	0	F	young	1.65		21	vehicle slow	2	1.65
	0	F	young	1.14		21	vehicle slow	2	1.14
	0	M	young	1.43		20	vehicle slow	2	1.43

Annexure 2

Pedestrian				Vehicle			Remark	wheeler	PET	Observed
Reach	Exit	Gender	Age	Reach	Exit	Speed				
0.56		F	young		0	37	stop	2	0.56	Highly Severe
0.63		F	young		0	33	stop	4	0.63	Highly Severe
0.68		M	young		0	39	stop	2	0.68	Highly Severe
0.78		F	young		0	30	no interaction	2	0.78	Normal
0.79		F	young		0	45	p slow	4	0.79	Severe
0.8		F	young		0	42	p slow	2	0.8	Severe
0.84		M	young		0	44	stop	4	0.84	Highly Severe
0.84		F	young		0	43	p slow	4	0.84	Severe
0.88		F	young		0	37	stop	3	0.88	Highly Severe
	0	F	young	0.88		27	vehicle slow	2	0.88	Severe
	0	F	young	0.9		41	p speed up	4	0.9	Highly Severe
0.92		M	young		0	35	stop	2	0.92	Highly Severe
0.93		F	young		0	42	p slow	4	0.93	Severe
	0	F	young	0.96		32	stop	2	0.96	Highly Severe
1		M	young		0	51	stop	4	1	Highly Severe
	0	M	young	1		33	no interaction	2	1	Normal
1.02		M	young		0	29	stop	2	1.02	Highly Severe
1.03		F	young		0	32	stop	4	1.03	Highly Severe
1.03		F	young		0	52	stop	4	1.03	Highly Severe
	0	M	young	1.04		31	no interaction	2	1.04	Normal
1.06		F	old		0	33	stop	2	1.06	Highly Severe
1.08		M	young		0	44	stop	2	1.08	Highly Severe
1.09		F	young		0	48	stop	4	1.09	Highly Severe
1.11		F	young		0	35	stop	2	1.11	Highly Severe
1.14		M	young		0	24	stop	4	1.14	Highly Severe
	0	F	young	1.14		21	vehicle slow	2	1.14	Severe
1.18		F	young		0	32	p slow	2	1.18	Severe
1.2		F	young		0	38	p slow	2	1.2	Severe
1.22		F	young		0	37	stop	4	1.22	Highly Severe
	0	M	young	1.23		40	no interaction	2	1.23	Normal
1.23		F	young		0	43	p slow	4	1.23	Severe
1.24		F	young		0	35	stop	2	1.24	Highly Severe
1.24		M	young		0	42	stop	4	1.24	Highly Severe
1.24		F	old		0	37	stop	2	1.24	Highly Severe
1.24		F	young		0	33	p slow	2	1.24	Severe
1.25		F	young		0	51	stop	4	1.25	Highly Severe
1.26		F	young		0	46	no interaction	2	1.26	Normal
1.27		M	young		0	33	stop	3	1.27	Highly Severe
1.27		F	young		0	38	stop	3	1.27	Highly Severe
1.27		M	young		0	36	stop	2	1.27	Highly Severe
	0	M	young	1.28		34	p speed up	2	1.28	Highly Severe
1.28		F	young		0	31	p slow	4	1.28	Severe
1.28		F	young		0	25	vehicle slow	2	1.28	Severe
1.34		F	young		0	44	p speed up	4	1.34	Highly Severe
1.34		F	young		0	42	stop	2	1.34	Highly Severe
	0	M	young	1.35		22	vehicle slow	2	1.35	Severe
1.36		M	young		0	26	stop	4	1.36	Highly Severe
1.37		M	young		0	38	stop	3	1.37	Highly Severe
1.38		M	young		0	38	stop	4	1.38	Highly Severe
1.38		F	young		0	37	stop	4	1.38	Highly Severe
	0	M	young	1.42		29	vehicle slow	4	1.42	Severe
	0	M	young	1.43		20	vehicle slow	2	1.43	Severe
1.46		M	young		0	39	stop	2	1.46	Highly Severe
1.47		M	young		0	39	stop	3	1.47	Highly Severe
	0	M	young	1.47		19	stop both	4	1.47	Highly Severe
1.49		F	young		0	41	p slow	4	1.49	Severe
1.5		F	young		0	35	stop	4	1.5	Highly Severe
1.5		M	young		0	43	stop	4	1.5	Highly Severe
	0	F	old	1.5		36	no interaction	2	1.5	Normal
1.53		M	young		0	28	stop	2	1.53	Highly Severe
	0	M	young	1.53		24	vehicle slow	2	1.53	Severe
1.54		M	young		0	44	stop	4	1.54	Highly Severe
	0	M	young	1.54		19	vehicle slow	2	1.54	Severe

1.57		F	young		0	31	p slow	4	1.57	Severe
1.59		F	young		0	41	stop	2	1.59	Highly Severe
1.61		M	young		0	40	stop	4	1.61	Highly Severe
	0	M	young	1.62		21	vehicle slow	2	1.62	Severe
1.63		F	young		0	37	stop	2	1.63	Highly Severe
1.63		F	young		0	37	stop	2	1.63	Highly Severe
	0	F	young	1.65		21	vehicle slow	2	1.65	Severe
1.66		F	young		0	38	no interaction	4	1.66	Normal
0.8		M	young	0.87	0	36	stop	2	1.67	Highly Severe
	0	M	young	1.69		32	p speed up	2	1.69	Highly Severe
1.69		M	old		0	52	p slow	2	1.69	Severe
1.71		M	young		0	43	stop	4	1.71	Highly Severe
1.77		M	old		0	35	p slow	2	1.77	Severe
	0	M	young	1.8		36	no interaction	2	1.8	Normal
	0	F	young	1.8		23	vehicle slow	2	1.8	Severe
1.81		M	young		0	37	stop	3	1.81	Highly Severe
1.84		M	old		0	45	stop	4	1.84	Highly Severe
	0	M	young	1.87		12	vehicle slow	2	1.87	Severe
1.89		M	young		0	45	stop	2	1.89	Highly Severe
1.9		F	young		0	30	stop	2	1.9	Highly Severe
1.9		F	young		0	28	stop	2	1.9	Highly Severe
1.91		M	young		0	36	stop	2	1.91	Highly Severe
	0	F	young	1.91		26	no interaction	2	1.91	Normal
	0	F	young	1.94		46	no interaction	2	1.94	Normal
2		F	young		0	35	stop	4	2	Highly Severe
2		F	young		0	39	stop	2	2	Highly Severe
2		F	young		0	43	stop	4	2	Highly Severe
2.02		F	young		0	42	stop	2	2.02	Highly Severe
2.04		M	young		0	43	stop	2	2.04	Highly Severe
2.05		F	young		0	42	no interaction	2	2.05	Normal
2.09		F	young		0	29	p slow	2	2.09	Severe
	0	M	young	2.12		20	p speed up	2	2.12	Highly Severe
2.14		F	young		0	41	stop	4	2.14	Highly Severe
	0	F	young	2.15		36	stop	2	2.15	Highly Severe
	0	F	young	2.15		36	no interaction	2	2.15	Normal
	0	M	young	2.18		39	no interaction	2	2.18	Normal
	0	M	old	2.26		45	no interaction	4	2.26	Normal
2.3		F	young		0	40	no interaction	2	2.3	Normal
	0	F	young	2.45		37	no interaction	2	2.45	Normal
	0	M	young	2.58		35	no interaction	2	2.58	Normal
	0	M	young	2.61		49	no interaction	4	2.61	Normal
2.63		F	young		0	32	stop	2	2.63	Highly Severe
	0	M	young	2.67		43	no interaction	3	2.67	Normal
	0	F	young	2.69		55	no interaction	4	2.69	Normal
2.77		F	young		0	41	stop	4	2.77	Highly Severe
2.86		M	old		0	35	stop	2	2.86	Highly Severe
2.98		M	old		0	28	stop	2	2.98	Highly Severe
	0	F	old	3		39	no interaction	2	3	Normal
3.02		F	young		0	33	stop	2	3.02	Highly Severe
	0	M	young	3.1		46	no interaction	4	3.1	Normal
	0	F	young	3.14		41	no interaction	2	3.14	Normal
	0	F	young	3.2		34	stop	2	3.2	Highly Severe
	0	F	young	3.24		44	no interaction	4	3.24	Normal
	0	M	young	3.28		40	no interaction	2	3.28	Normal
	0	F	young	3.31		51	no interaction	4	3.31	Normal
	0	M	young	3.33		40	no interaction	2	3.33	Normal
	0	F	young	3.37		38	no interaction	2	3.37	Normal
	0	F	young	3.4		42	no interaction	2	3.4	Normal
	0	M	young	3.42		43	no interaction	4	3.42	Normal
	0	M	young	3.74		44	no interaction	2	3.74	Normal
	0	F	young	3.92		42	no interaction	2	3.92	Normal
3.94		M	young		0	42	no interaction	2	3.94	Normal
4.03		M	old		0	33	p slow	2	4.03	Severe
4.19		F	young		0	48	no interaction	2	4.19	Normal
	0	F	young	4.87		14	no interaction	2	4.87	Normal
	0	F	old	4.97		40	no interaction	2	4.97	Normal
	0	F	young	5.33		15	vehicle slow	4	5.33	Severe
	0	M	young	5.5		10	vehicle slow	4	5.5	Severe
	0	M	young	6.1		38	no interaction	2	6.1	Normal

Annexure 3

Pedestrian				Vehicle			Remark	wheeler	PET	Observed	Predicted
Reach	Exit	Gender	Age	Reach	Exit	Speed					
0.62		F	young		0	31	stop	2	0.62	Highly Severe	Highly Severe
0.77		F	young		0	45	stop	4	0.77	Highly Severe	Highly Severe
0.82		M	young		0	34	stop	4	0.82	Highly Severe	Highly Severe
0.97		M	young		0	38	stop	4	0.97	Highly Severe	Highly Severe
0.99		M	young		0	38	stop	2	0.99	Highly Severe	Highly Severe
1		M	young		0	46	stop	4	1	Highly Severe	Highly Severe
1		F	young		0	33	stop	4	1	Highly Severe	Highly Severe
	0	M	young	1.04		32	p speed up	4	1.04	Highly Severe	Highly Severe
	0	M	young	1.91		32	p speed up	2	1.91	Highly Severe	Normal
	0	F	young	1.99		36	p speed up	2	1.99	Highly Severe	Normal
2.93		F	young		0	38	stop	3	2.93	Highly Severe	Normal
	0	F	young	1.08		42	p speed up	4	1.08	Highly Severe	Severe
1.32		M	young		0	38	stop	4	1.32	Highly Severe	Severe
1.43		F	young		0	37	stop	2	1.43	Highly Severe	Severe
1.45		F	young		0	32	p speed up	2	1.45	Highly Severe	Severe
1.46		M	young		0	33	stop	2	1.46	Highly Severe	Severe
1.54		F	young		0	39	stop	4	1.54	Highly Severe	Severe
1.68		M	young		0	29	stop	2	1.68	Highly Severe	Severe
2.15		F	young		0	39	no interaction	2	2.15	Normal	Normal
2.24		F	young		0	40	no interaction	2	2.24	Normal	Normal
	0	M	young	2.32		47	no interaction	2	2.32	Normal	Normal
	0	F	young	2.4		44	no interaction	2	2.4	Normal	Normal
	0	F	young	2.56		44	no interaction	3	2.56	Normal	Normal
	0	F	young	2.66		35	no interaction	2	2.66	Normal	Normal
	0	M	young	3		38	no interaction	4	3	Normal	Normal
3.93		M	young		0	43	no interaction	2	3.93	Normal	Normal
	0	M	young	4.78		15	no interaction	4	4.78	Normal	Normal
	0	F	old	5.51		40	no interaction	2	5.51	Normal	Normal
	0	M	young	7.54		40	no interaction	2	7.54	Normal	Normal
0.86		F	young		0	41	p slow	4	0.86	Severe	Highly Severe
0.87		F	young		0	40	p slow	4	0.87	Severe	Highly Severe
	0	F	young	1.16		22	vehicle slow	4	1.16	Severe	Severe
1.2		F	young		0	36	p slow	2	1.2	Severe	Severe
1.28		M	young		0	34	p slow	4	1.28	Severe	Severe