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Research Article

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Impact of Traffic Characteristic at Unsignalized Intersection in Mixed Traffic Condition using Logistic Regression Method (LRM) and Artificial Neural Network (ANN)

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Abstract

This research aims to investigate blackspot location at the chosen unsignalized intersection site (S) and the progression of right-turn motor vehicles (RMV) using the logistic regression method (LRM) and artificial neural network (ANN). In the initial stages, eleven unsignalized intersection site (S) were selected as the blackspot location and the study concentrating on urban road network. The network recognizes as heterogeneous road that all vehicle category utilizing same network. Consequently, the traffic conflict (TC) is analysed with a focus type of conflict, TC frequency at different time and sites. An LRM and ANN model were developed for right-turn motorists using datasets by combining three unsignalized intersection site (S2, S9 and S10). They are all vehicle (AV) model which consist (841 datasets), Passenger Car Model involved (357 dataset) and Motorcycle Model content (399 dataset). Using this approach, the identification of the variables that influence the decision-making process of right-turn motor vehicles (RMV) was done. Furthermore, the measurement of critical for vehicle category were implementing LRM approach. Among the sixteen variables examined in this statistical model, we found that vehicle gap, channelization (Chlzation), second vehicle passing RMV is motorcycle (SMc), second vehicle passing RMV is motorcycle (SCar), angular conflict (AGc), rear-end conflict (REc), traffic volume (TV) and RMV is rider were significant. This study purpose by implementing intelligent vehicle equipped with internet of thing (IoV), vehicle to vehicle communication (V2V) and advanced driver assistance system (ADAS) might solve partially traffic conflict and as well as traffic accident.

Keywords: Logistic Regression Method, Artificial Neural Network, Internet of Things and Vehicle to Vehicle Communication

1. Introduction

Smart city consists a variety of innovative technologies to manage the infrastructure such as transportation, asset, electricity supply, telecommunication, building and network. The latest technology to support smart city in transportation was internet of vehicle (IoV). The interesting part of (IoV) were the ability to create network of information interaction among vehicles, surrounding environment and roadside infrastructure trough wireless communication, satellite, and sensing technology. The data output from vehicular devices represents the traffic condition (traffic congestion, traffic accident, re-route the network, public transport delays) in real time series. Realizing the potential of IoV, in solving the traffic congestion, low energy efficiency, traffic safety, optimizing traffic flow, and traffic signal malfunction. The integration of expert from information communication technology, energy, mechanical, electrical, and civil engineering would be a best solution to overcome the complexity of the transportation system in smart city.

Mobile infrastructure defines as ITS element without static network connection such as vehicles. Recently, vehicles on roadways categories into three range from classic passenger cars unequipped digital system (traditional), fully autonomous (intelligent) and unmanned vehicle (intelligent). Traditional vehicles are not facilitated with vehicle-to-vehicle communication (V2V), vehicle to infrastructure (V2I) and Infrastructure to vehicle (I2V). Meanwhile, intelligent vehicles are provided with V2V or V2I interaction.

Usually, intelligent vehicles are included V2V and V2I package that are handled by human driver. Device like on-board sensor were fit in the vehicle and has capability to observe the location and behaviour of surrounding vehicles as well as recognize the obstacle and road defects. Analyse collection of the data by using on-board processing and storage system. In addition, ITS infrastructure via roadside unit (RSU) and information surrounding vehicles were utilized to collect more data information. IEEE 802.11p protocol, is used for RSU meanwhile short-range communication with nearest vehicles. The longer-range communications via IEEE 802.16p protocol, WiMAX, GSM, 6G or Satellite. Normally this medium is used to communicate with the traffic management centre or other sources.

IoT function in smart cities, to provide life easier for the people in daily activities. Moreover, IoT devices supporting data collection and filtering the correct information to the user in smart cities [1]. Smart city application included intelligent traffic system (ITS), smart grid, smart home automation, smart healthcare, traffic environment monitoring, smart supply chain and smart agriculture [2]. The challenge, handling the big data become complicated because of limited storage, low computation power, less transmission range and vulnerability to attack are some of the issues of IoT devices. However, some systems have been developed to manage the data and devices [3]. Cluster head is one of the methods used to overcome this issue. Hitherto, this approach also has some weakness such as vast data storage, scalability, and information processing [4]. Moreover, the constraint in handling centralized system is transparency, trust, single point of failure and data integrity. Thus, to monitor these issues edge computing servers and blockchain are suitable approach [5].

New blocks will be provided and it is unassailable, when the transaction of blockchain is accomplish [6]. In the blockchain, the predecessor blocks with hash value are presented and remind with the past transaction history. In distribute manufacturing process, blockchain and cloud methods are synergized [7]. By integrating cloud-based supply chain managements (SCMs) with blockchain can restore unassailable archives and records [8].

The variety modes of transportation involving bicycles, motorcycles, passenger cars, vans, buses, and lorries are sharing on same road and intersection describe to mixed traffic or heterogeneous. The integration of traditional vehicle, connected automated vehicle (CAVs), and autonomous vehicle (AVs) corporately content a dynamic and responding mixed traffic system. The effect rising of traffic density would create scenario of traffic fluctuation in which vehicles rotation between decelerating and accelerating despite steady driving state and comfortable [9,10].

Intelligent vehicle (IV) in Figure 1, shown the performance equip with advance driver assistance performances system (ADAS), function to support vehicle from traffic conflict and accident prevention approach. Precisely, vehicles have capabilities to map and measures the distance, speed, and angle of arrival (AOA) of variety direction in dynamic and different situation. Technologies in ADAS consist optical cameras, radio detection and radar, light detection and ranging (LIDAR), long range radar and ultrasonic sensors are among highly accurate environment awareness [11-14]. The advantage using radar because it has a robust and affordable technology that simultaneously measures the velocity, range, distance, angle of arrival (AOA) of multiple targets under worst lightning condition [15]. The application from automotive radar includes rear and front cross traffic alert (CTA), blind spot detection (BSD), adaptive cruise control (ACC), and automatic emergency braking (AEB) system.

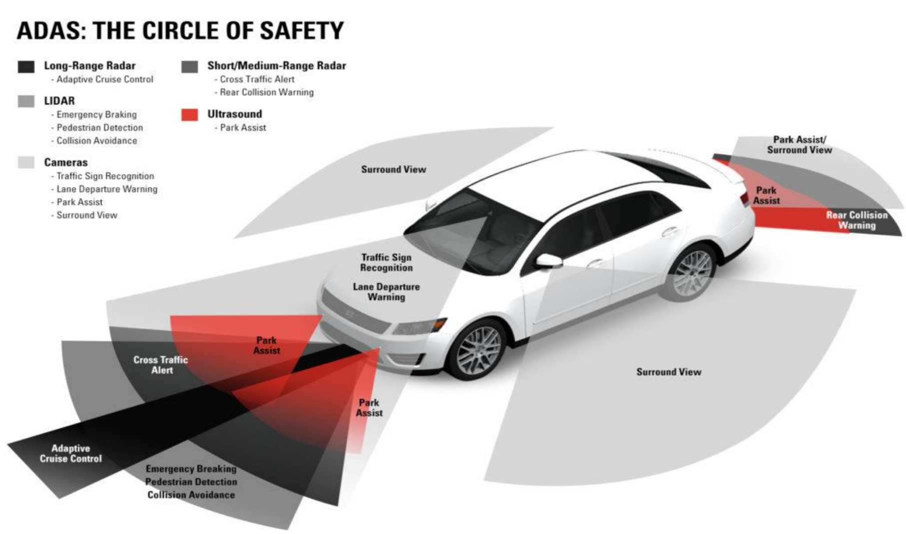

Figure 1: Active or Passive Device for Advanced Driver Assistance System (ADAS) in Today and Future Vehicles

Providing both channelization and signalization of the turn-right could improve lane discipline. Precisely, by separating drivers who intend to turn right and those who continue onto straight movement [16,17]. Previous studies carried out by has identified the traffic characteristic for right-turn motor vehicles (RMV) from minor road onto main stream at unsignalized intersection site (S) was the most hazardous manoeuvre [18-24]. The RMV model have been developed by adopting Logistic Regression Method (LRM), Structural Equation Model (SEM), Smart Partial Least Square (PLS-SEM) and Artificial Neural Networks (ANN). However, those study did not emphasize traffic volume, and conflict study.

Human, vehicle, and roadways play a major role in road accident. Beside that other factor such as transportation issue, weather, and lighting also contribute to crash. Federal Highway Administration (FHWA) has been highlighting the essential element of human, vehicle, and roadway due to significance influence on road safety analysis [25].

This paper is organized as follows. Section 2 consist data collection. In Section 3 involved type of conflict, analysis of traffic conflict, and traffic conflict frequency at different time and site. Next, Section 4 development of logistic regression method, development of critical gap model, calculate critical gap and construction of all vehicle model by adopting artificial neural network. Section 5 include discussion of the study and lastly Section 6 was conclusion.

2. Data Collection

Malaysia Federal Route 50 has been selected in this study. The infrastructure has been designing four-lanes with two-carriage ways. The roadway stretches connecting several cities from Batu Pahat, Ayer Hitam, Parit Raja and Kluang about 60 kilometres. In year 2024, It has capacity of providing roughly 91,709 veh/day and around 9,100 veh/hr. The design speed for this infrastructure is approximately 100 kph. In this study, eleven unsignalized Intersection site (S) has been chosen for traffic survey using video camera recording namely S2, S5, S8, S9, S10, S19, S20, S21, S22, S23, and S24. The location of site divided in two province which is in urban area and sub-urban area. In urban region include S2, S5, S8, S9 and S10 meanwhile in sub-urban district involved S19, S20, S21, S22, S23, and S24. The selection of the sites was based on blackspot location situated at Federal Route 50. Traffic volume (TV) has been carried out at each site and concentrate on three peak hours namely morning (8:00-10:00), midday (12:00-14:00) and afternoon (16:00-18:00). Total of 66 hours traffic survey is required to complete the task on the flied work at eleven sites. The total number of traffic involved in the survey was 305,311 vehicles. Furthermore, the microscopic analysis of the vehicle classification, traffic manoeuvre, pedestrian crossing, traffic conflict (TC) and approach speed were executed or analyse in the laboratory. They are five types of vehicles in traffic survey was counted separately such as motorcycle, passenger car, van, small lorry, heavy lorry, and bus. All traffic classification and vehicle manoeuvres were analysed simultaneously. In this study, the heterogeneous traffic condition occurred with dynamic and static vehicles characteristic utilizing the same road space. The smaller vehicle like motorcycle commonly try to ride through the gap available between larger vehicles.

2.1. Heterogeneous Traffic Frequency

Matlab is an interactive programming environment with graphical output. The mathematical softwareMatlab is widely use in all area of education, research, and industry. It has a powerful graphic tool and can produce both 2D and 3D. Figure 2, illustrate the 2D frequency for heterogeneous traffic variables. In the 2D diagram consist 28 variables that perform its fluctuation rate. Out of 28 predictors only 8 parameters were found significance as discuss in Section 4.0 and Section 4.3. XY axis in the 2D graph define as datasets, and frequency respectively. The input and output parameter are right-turn motor vehicle (RMV), Gap, second vehicle passing RMV is passenger car (SCar), second vehicle passing RMV is motorcycle (SMc), angular conflict (AGc), rear-end conflict (REc), traffic volume (TV), speed limit less than 57 km/hr (SPLT57) and traffic signal (TSignal).

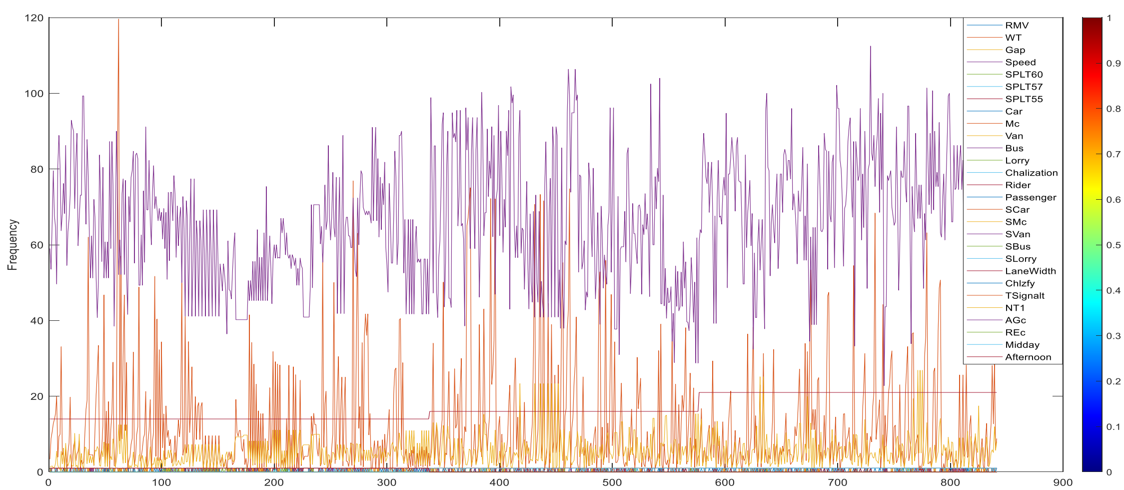

Figure 2: 2D Diagram of Heterogeneous Traffic Frequency

In addition, the matlab, have an advantage to plot 3D Bubble Charts for multiple variable data analysis by using three axes (X= logistic data, Y= speed and Z=gap). 3D Bubble Chart demonstrate colouring bubble to visualize the parameter. The distribution binary data (0 or 1) indicate value 1 influence the bubble fluctuation compare with value 0, as shown in Figure 3. In the logistic data, value 0 mean the rejected gap meanwhile value 1 define as accepted gap. In the bubble chart acceptance gap range approximately from (0-30 seconds) meanwhile rejected gap range from (0- 10 seconds). Furthermore, from bubble chart observation approach speed for rejected gap indicate more higher compare to accepted gap. Consequently, the distribution for blue and red bubble is dominant in value 1 area compare with value 0 area.

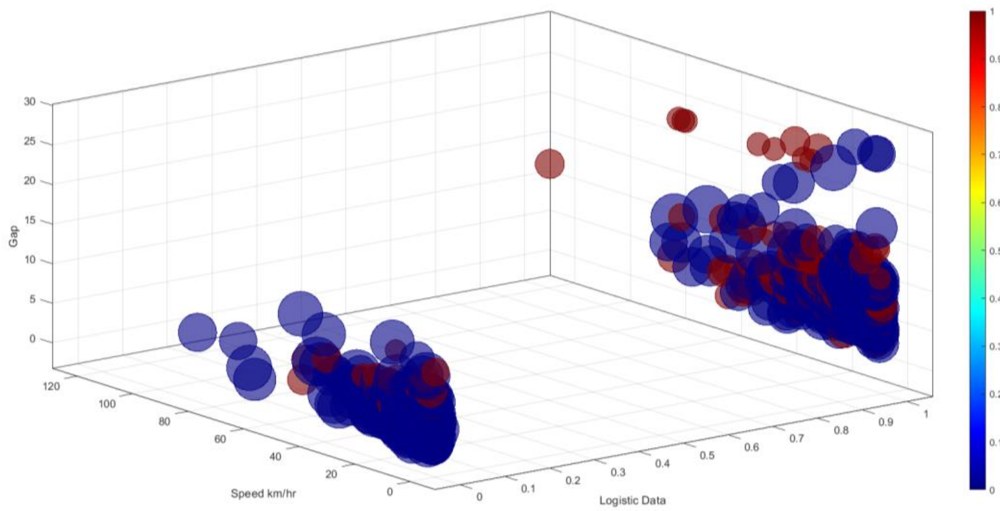

Figure 3: 3D Bubble Chart for Traffic Variable Distribution

3. Traffic Volume

Figure 4 illustrates the fluctuation of traffic volume at eleven site measure in unit vehicle per hour (veh/hr). Meanwhile, Figure 5 represents map diagram of traffic volume, for easy understanding and clear visualization of traffic mapping at each site. In the geometry mapping graph base on the colour (blue, orange, grey, yellow, and light blue) as traffic frequency. Traffic volume (TV) which occurred in the two highest locations at Site 5 and Site 21 received 9,078 veh/hr and 8,560 veh/hr respectively. Moreover, around late afternoon (17:00-18:00), it recorded the highest trend among other time series. In Figure 4, The range for traffic volume during afternoon between (4,670 veh/hr – 9,078 veh/hr). The highest TV for Site 5, Site 21, Site 2, Site 22, Site 8, Site 9, Site 20, and Site 19 was 9,078 veh/hr, 8,560 veh/hr, 8,167 veh/hr, 7,820 veh/hr, 7,650 veh/hr, 7,426 veh/hr, 7,041 veh/hr and 6,747 veh/hr respectively. Meanwhile the lowest frequency of TV which is in late afternoon (17:00-18:00) at Site 10, Site 23, and Site 24 stated 3,771veh/hr 4,670 veh/hr and 4,714 veh/hr respectively. The lowest traffic trend volume among time interval is detected in the morning (9:00-10:00). The TV trend during this time shows uniform flow for each site with the range between (2,678 veh/hr – 5,211 veh/hr).

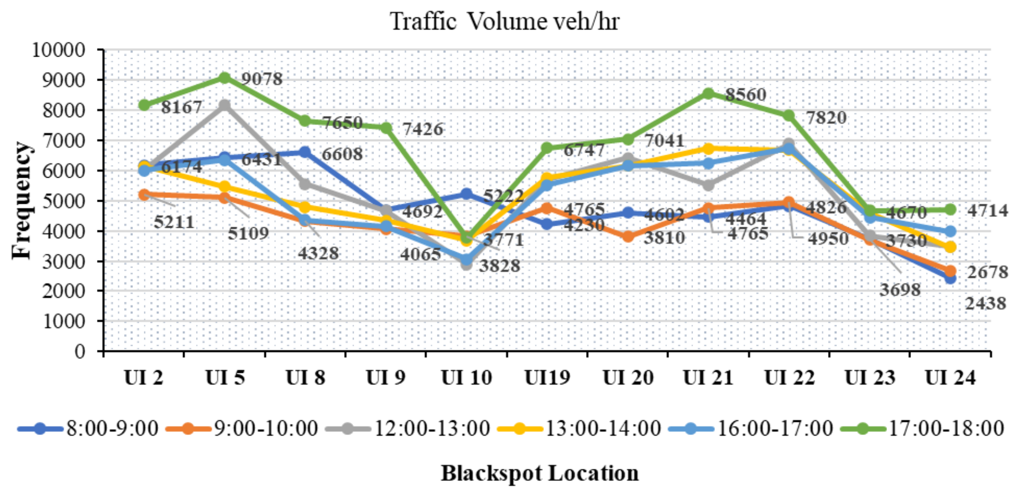

Figure 4: Traffic Volume at Blackspot Location Over Six Hours Survey in a Typical Weekday

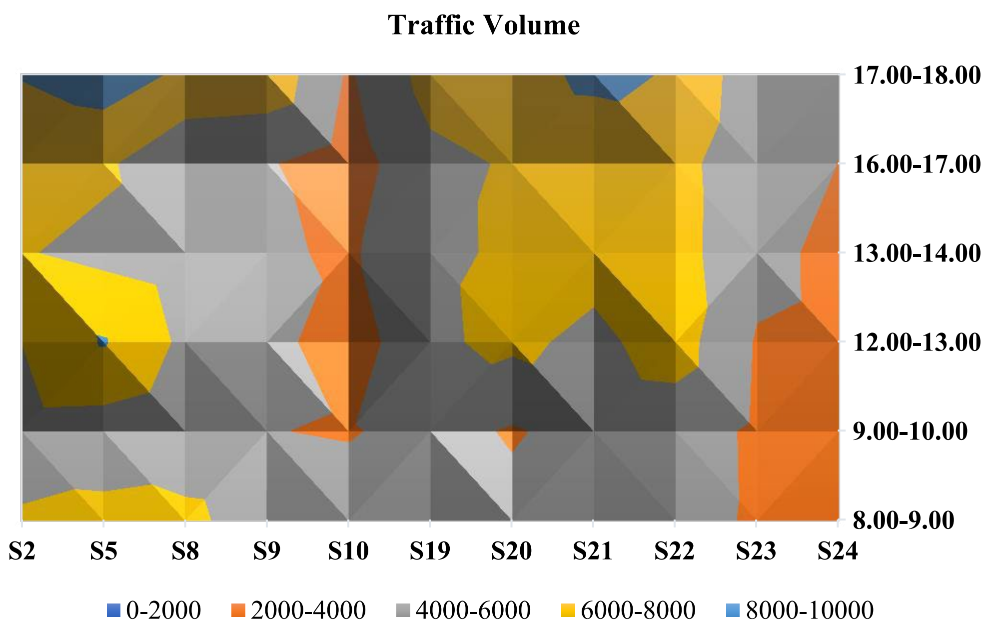

Figure 5: Map Diagram of Traffic Volume at Blackspot Location Over Six Hours Survey in a Typical Weekday

3.1. Type of Traffic Conflict

The accident risk is possibly associated with varies aspect. One of the factors were driving behaviour leading vehicles and following vehicles. The hazardous also may contribute from drivers turning decision from minor road onto mainstream road and consequently from mainstream to minor road. Traffic conflict (TC) define as several circumstance relating two or more vehicles such as immediate braking or weaving, slippery action and drastic lane change to avoid collision. Types of conflicts in these studies were simplifies into three types namely right-turn, rear-end conflict and head-on conflict as summarize in Table 1. In this study, TC concentrating on three categories manoeuvre such as right turn from minor road, left turn from minor road and right turn from mainstream. The impact of right turn conflict from minor road will associate with three type of risk, TC 1(angular or right-turn conflict), TC 3b (rear-end conflict), TC 3c (rear-end conflict) as illustrate in Figure 6. meanwhile TC 2 define as angular or right-turn conflict from mainstream. Secondly, the effect of left-turn from minor road may related with TC 3a (rear-end conflict). Thirdly, TC 4 (head on conflict) this situation happens when vehicle in lane two decide to overtake vehicle ahead by entering lane three and simultaneously meet incoming vehicle from lane three.

Type of Risk	Description
TC1	Angular or right-turn conflict
TC2	Angular or right-turn conflict from mainstream
TC3a	Rear-end conflict
TC3b	Rear-end conflict
TC3c	Rear-end conflict
TC4	Head on conflict

Table 1: Type of Risk

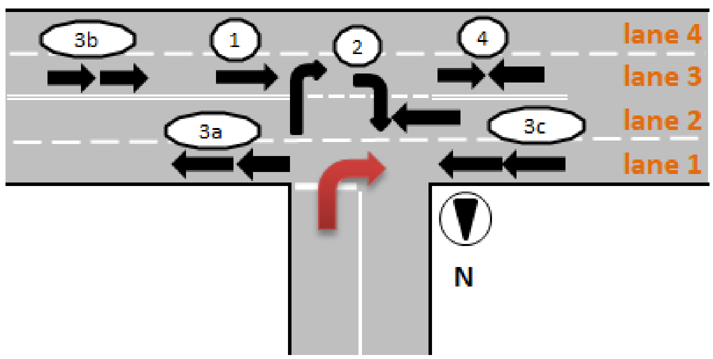

Figure 6: Type of Traffic Conflict (TC1=right-turn, TC2= right-turn, TC3a, TC3b, TC3c =rear-end, TC4=head-on)

3.2. Traffic Conflict Frequency

Figure 7 illustrates the selection of eleven sites based on the blackspot ranking on Federal Route 50. The S2, S5, S8, S9 and S10 represent urban areas, while S19, S20, S21, S22, S23, and S24 are in sub-urban areas. It was found that most of the TC is due to the rear-end (84.9%), followed by right-turn (13.9%), and head-on (1.2%). The highest number of rear-end conflicts was at S22, S19, and S21, with 46, 41, and 30 cases, respectively. It was noticeable that less angular conflict occurs, with the highest cases recorded at S10. Meanwhile, head-on conflicts only appeared in S20 and S2, with a total of 3 cases.

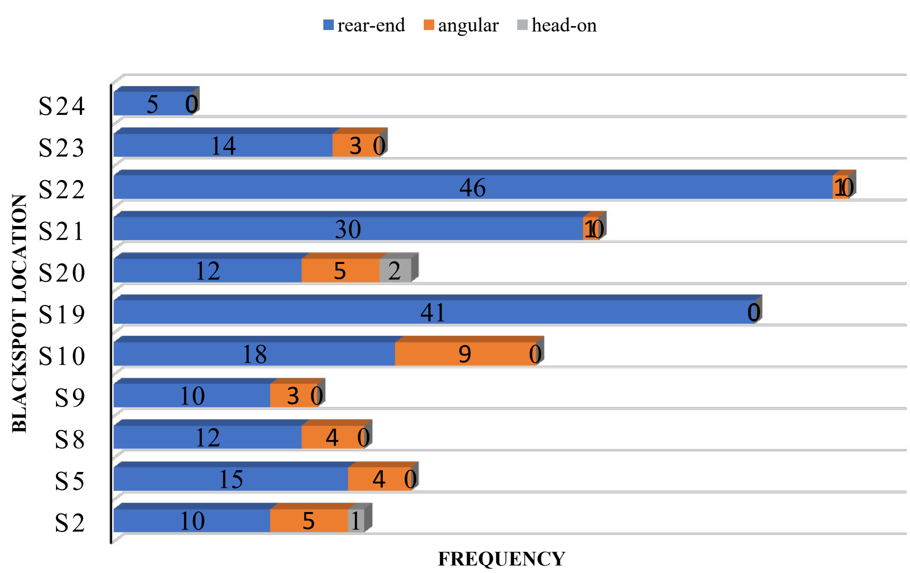

Figure 7: Traffic Conflict Frequency

3.3. Traffic Conflict Frequency at Different Time and Site

Figure 8, illustrated the frequency of traffic conflict at each site. The maximum number of traffic conflict (TC) was S22 stated total 47 cases (morning=6, midday=17 and afternoon=24). S19 experience second higher of TC with total 36 cases (morning=9, midday=13 and afternoon=14). Next, S21 has been detected third highest of TC with total 31 cases (morning=6, midday=7 and afternoon=18). Following by S10, received total of 27 cases (morning=7, midday=2 and afternoon=18). S20 and S5 share the equal total of TC with 19 cases. Meanwhile S23, S8, S2, S9, and S24 obtained TC with total 17 cases, 16 cases, 16 cases, 13 cases and 5 cases respectively. The highest case often occurred in the afternoon, midday and morning recorded 123 cases, 72 cases and 51 cases respectively. In Afternoon, probably because of higher traffic density, its time people return home, fatigue factor and traffic congestion. Most cases occurred at S22, S21, S19 and S10 because those intersection situated at industrial, residential area and education hub.

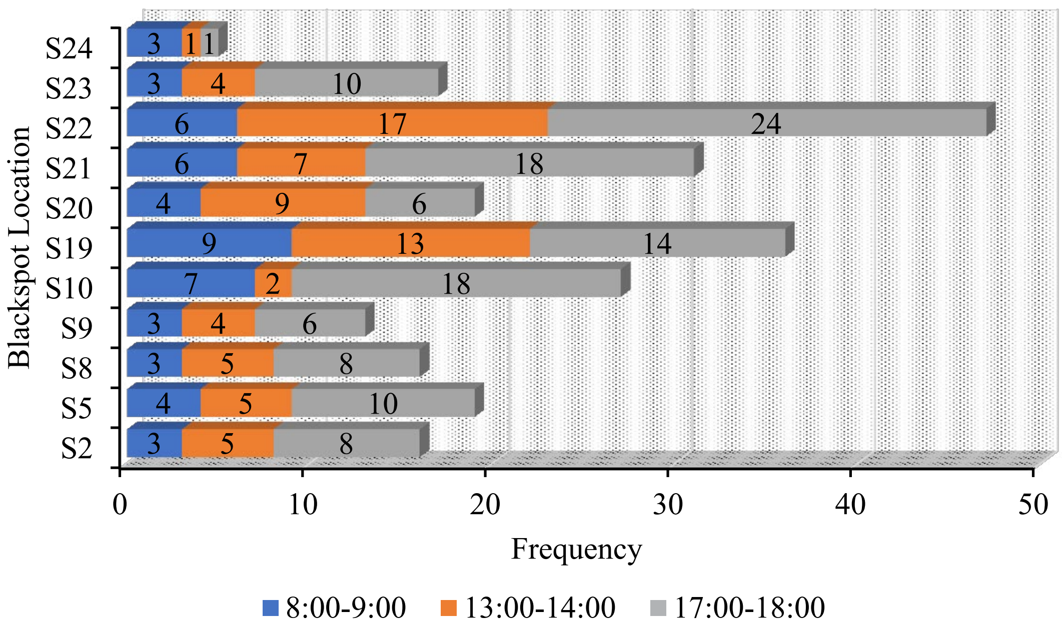

Figure 8: Traffic Conflict Base on Time Circumstance

4. Development of Logistic Regression Method

In the construction of RMV Models, emphasizing urban area involving S2, S9 and S10. They are three model with three categories' datasets. First Model concentrate on passenger car (PC) content 257 datasets (225 rejected gaps and 174 accepted gaps). Second model focus on motorcycle involved 399 datasets (219 rejected gaps and 170 accepted gaps). Third model emphasize on All Vehicle (AV) contain 841 datasets (480 rejected gaps and 361 accepted gaps). Following this, in Model 1 gap, the motorcycle as the second vehicle passing the RMV (SMc), rear-end conflict (REc), traffic volume (TV) and channelization (Chlzation) were selected as the independent variables or predictors. Next, in Model 2 five predictors selected which is gap, the motorcycle as the second vehicle passing the RMV (SMc), the passenger car as the second vehicle passing the RMV (SCar), angular conflict (AGc) and traffic volume (TV). Meanwhile, in AV Model eight independent variables were selected which is gap, the motorcycle as the second vehicle passing the RMV (SMc), the passenger car as the second vehicle passing the RMV (SCar), angular conflict (AGc), rear-end conflict (REc), and traffic conflict (TV), rider and channelization (Chlzation). RMV is the dependent variable in logistic regression, which was set to 1 if present and 0 if otherwise, as shown in Table 2. Model validation was performed using SPSS Statistics 26. A stepwise selection procedure was used to establish the significance intervals of 90%, 95%, and 99%. The descriptions of all dependent and independent variables are given in Table 2.

Abbr.	Description
RMV	RMV=1 if motor vehicles turned right at a gap acceptance, but 0 if not.
Gap	Gap which is rejected or accepted (sec).
Car, Mc, Rider, Van, Lorry, and Bus.	Car, Mc, Rider, Van, Lorry and Bus=1 if the RMV is car, and 0 if otherwise.

SCar, SMc, SBus, SLorry, SVan	Second vehicle is passenger car, motorcycle, bus, lorry and van passing the RMV on the major road
Gap1,2,3,4,5	If the gap was gap pattern 1,2,3,4,5 in Fig. 4, Gap1,2,3,4 and 5 =1, but 0 if not.
Chlzation	If channelization facility is in unsignalized intersection, so Chlzation = 1, but 0 if not.
AGc	If angular conflict (AGc) detect=1, but 0 if not
REc	If rear-end conflict (REc) detect=1, but 0 if not
TV	Traffic volume (veh/hr) for each selected site.

Table 2: Attributes of Traffic Behaviour Models

Table 3 shown the coefficient, T-Stat and significance of the parameter in the Model. In Model 1 (Passenger Car), three variable which is Gap and Chlzation remark significant level at 99%. However, (SMc) received significance level at 95% meanwhile REc and TV obtained significant level at 90%. Model 2 (Motorcycle), all predictor which is Gap, SMc, SCar, REc, AGc and TV received significance level at 99%. Lastly Model 3 (All Vehicle), each variable which is Gap, SCar, SMc, AGc, REc, Chlzation, and Rider found significance level at 99%. However, only TV obtained significance level at 95%.

	Passenger Car (PC) Model 1	Motorcycle (MC) Model 2	All Vehicle (AV) Model 3
Constant	-7.44 (31.799)***	-8.443 (32.295)***	-7.609 (68.573)***
Gap	0.970 (87.244)***	0.835 (103.883)***	0.915 (212.467)***
SCar	-	1.367 (12.523)***	0.72 (6.493)***
SMc	1.304 (3.987)**	1.864 (7.984)***	1.552 (11.738)***
AGc	-	3.065 (7.227)***	3.243 (8.603)***
REc	2.710 (3.202)*	-	3.595 (9.663)***
TV	0.001 (2.916)*	0.001 (5.467)***	0.001 (4.879)**
Rider	-	-	0.699 (8.471)***
Chlzation	-2.105 (10.884)***	-	-1.160 (8.471***)
N	357	399	841
NagelkerkeR^2	0.73	0.63	0.70
H.R-Right Turn	84.50%	77.60%	82.50%
H.R-Total	89.00%	82.00%	86.80%

*, **, ***=Significant at the 90%,95% and 99% level, respectively

Table 3: Logistic Regression Models for Right-turn Motor Vehicles (RMVs)

In Model 1 negative sign of Chlzation mean that RMV likely to accept longer gap. Conversely, a positive sign of gap, second vehicle is motorcycle passing the RMV on the major road (SMc), rear-end (REc) and traffic volume (TV) can be interpreted that RMV is likely to accept a shorter gap. In Model 2, a positive value for gap, second vehicle is motorcycle passing the RMV on the major road (SMc), second vehicle is passenger car passing the RMV on the major road (SCar), angular conflict (AGc) and traffic volume (TV) stipulates that RMV is more likely to accept a shorter gap. In AV Model, negative value of (Chlzation), indicate that RMV likely to accept longer gap acceptance. Meanwhile, positive value of gap, second vehicle is motorcycle passing the RMV on the major road (SMc), angular conflict (AGc), rear-end conflict (REc), and rider stipulates that RMV is more likely to accept a shorter gap. R square (R2) for model passenger car (PC), motorcycle (MC) and all vehicle (AV) received 0.73, 0.63 and 0.70 respectively indicated the data fit in the model quite well. The higher value of R2 indicate the Model excellent performance as in Equation 1.

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

4.1. Development of Critical Gap Model

The analysis of critical gap involved five category vehicle dataset, passenger car (357 dataset), motorcycle (399 dataset), rider (276 dataset), van (47 dataset), lorry (33 dataset) and all vehicle (481 dataset). Table 4, shows the development of logistic regression models, concentrating on RMV for all vehicle category. The purpose of (Model 4- Model 9) is to obtain the critical gap for each vehicle classification. The probability of the selected each type of vehicle accepting gap, (P_{rmv}) using logistic function in given in the equation below:

$$P_{rmv}(i) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}} \tag{2}$$

where β_o = constant, β_1, β_2, and β_3 = is the regression coefficient, X_1, X_2, X_3 and X_n = other dependent variables. Previous researchers (Gattis et. al., 1998) have justified the critical gap as that gap for which the probability of accepting is 0.5. Based on logit function in Equation 2, can be converted into a linear equation as stated below:

$$\text{In}\left(\frac{P_{rmv}}{1 - P_{rmv}}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{3}$$

Logic function or logistic regression as in Equation 3, is applied for to the same dataset as shown in Table 4, the following predictive equation for each various of vehicle are established:

$$P_{pc} = \text{In}\left(\frac{P_{rmv}}{1 - P_{rmv}}\right) = -5.07 + 0.86x \tag{4}$$

$$P_{mc} = \text{In}\left(\frac{1 - P_{rmv}}{1 - P_{rmv}}\right) = -3.87 + 0.75x \tag{5}$$

$$P_{rider} = \text{In}\left(\frac{p_{rmv}}{1 - p_{rmv}}\right) = -3.51 + 0.74x \tag{6}$$

$$P_{van} = \text{In}\left(\frac{p_{rmv}}{1 - p_{rmv}}\right) = -7.96 + 1.65x \tag{7}$$

$$P_{lorry} = \text{In}\left(\frac{p_{rmv}}{1 - p_{rmv}}\right) = -7.29 + 1.16x \tag{8}$$

$$P_{av} = \text{In}\left(\frac{p_{rmv}}{1 - p_{rmv}}\right) = -4.49 + 0.82x \tag{9}$$

$$P_{pc} = \text{In}\left(\frac{p_{pc}}{1-p_{pc}}\right) = -7.440 + 0.970x + 1.304(\text{SMc}) + 2.710(\text{REc}) + 0.001(\text{TV}) - 2.105(\text{Chlzation}) \quad (10)$$

$$P_{mc} = \text{In}\left(\frac{p_{mc}}{1-p_{mc}}\right) = -8.443 + 0.835x + 1.367(\text{SCar}) + 1.864(\text{SMc}) + 3.065(\text{AGc}) + 0.001(\text{TV}) \quad (11)$$

$$P_{av} = \text{In}\left(\frac{p_{av}}{1-p_{av}}\right) = -7.609 + 0.915x + 0.720(\text{SCar}) + 1.552(\text{SMc}) + 3.243(\text{AGc}) + +3.595(\text{REc}) + 0.001(\text{TV}) - 1.160(\text{Chlzation}) \quad (12)$$

Attributes	PC Model 4	MC Model 5	Rider Model 6	Van Model 7	Lorry Model 8	AV Model 9
Constant	-5.07 (94.96)***	-3.87 (103.81)***	-3.51 (66.89)***	-7.96 (9.01)***	-7.29 (6.24)***	-4.49 (228.94)***
Gap	0.86 (97.79)***	0.75 (103.81)***	0.74 (72.25)***	1.65 (8.83)***	1.16 (5.84)***	0.82 (219.22)***
N	357	399	276	47	33	841
NagelkerkeR^2	0.70	0.57	0.55	0.87	0.78	0.64
H.R-Right Turn	82%	75%	78%	88%	77%	78%
H.R-Total	88%	82%	81%	89%	85%	84%

*, **, ***=Significant at the 90%,95% and 99% level, respectively

Table 4: Logistic Regression Models for Critical Gap

4.2. Critical Gap

The estimated critical gaps for RMVs, were defined by gap accepted with probability (P_rmv) equals to 50% as shown in Table 4. Model 4 (Equation 4), Model 5 (Equation 5), Model 6 (Equation 6), Model 7 (Equation 7), Model 8 (Equation 8), and Model 9 (Equation 9) were used to calculate the critical gap for passenger cars, motorcyclists, riders, vans, lorries, and all vehicle respectively by including (P_rmv) = 0.5 for each of the models. Table 5 shows the summary of critical gap for RMVs. The result of critical passenger cars, motorcyclists, riders, vans, lorries, and all vehicle were 5.87 seconds, 5.16 seconds, 4.74 seconds, 4.82 seconds, 6.18 seconds, 4.48 seconds respectively. Consequently, critical gap for all type of vehicles was less than 6 seconds except lorry comparing with Malaysia Standard (ATJ 11/87) and United State Highway Capacity Manual 2000 (USHCM 2000) requirement 7 seconds and 7.5 seconds, correspondingly [26,27]. Which mean the critical gap for RMVs did not comply the condition for both standard. Critical gap for rider stated the lowest among the other traffic user with 4.74 seconds meanwhile the higher critical gap was lorry obtained 6.18 seconds.

Right Turning Motor Vehicles (RMVs)	Critical Gap (t_c)(seconds)
Passenger car	5.87
Motorcycle	5.16
Rider	4.74
Van	4.82
Lorry	6.18
All vehicle	5.48
Passenger car, traffic volume and rear-end conflict	2.83
Motorcycle, traffic volume and angular conflict	2.81
All vehicle, traffic volume and rear-end conflict	1.69

Table 5: Critical Gap for Vehicles

Meanwhile, to measure critical gaps for passenger car with traffic volume and rear-end conflict, motorcycle with traffic volume and angular conflict, lastly all vehicle with traffic volume and rear -end conflict implementing Model 1 (Equation 10), Model 2 (Equation 11) and Model 3 (Equation 12) by setting (P_{rtm}) = 0.5 in the formula. Furthermore, set traffic volume (TV), angular conflict (AGc), and rear end conflict (REc) =1 and other variable equal to 0. The results for passenger car (PC), motorcycle (MC), and all vehicle (AV) were 2.83 seconds, 2.81 seconds, and 1.69 seconds respectively.

4.3. Artificial Neural Network Model

The purpose of this research is to ascertain the link between the analysed inputs and the outcomes. The result for right-turn motor vehicles (RMVs) transitioning from a minor road to a major route near selected unsignalized intersection site (S) on the Urban Network. Total number 841 of gap acceptance RMVs were used in the analysis. They are 8 input predators selected in the analysis namely gap, channelization (Chlzation), second vehicle allowing RMV is passenger car (SCar), second vehicle allowing RMV is motorcycle (SMc), angular conflict (AGc), rear-end conflict (REc), rider, and traffic volume (TV).

The association between the input and output was represented by the artificial neural networks. This method is used in the framework of regression, which requires a more complex methodology like probit or logit. For the study, SPSS 26 software was used to conduct the analysis as it had the capability to perform artificial neural network analysis. The process requires both dependent and independent variables to be entered. Then, it is critical to choose the program route. Three processes are involved in this process: analysis, neural networks and multilayer perceptron. In this section, right-turn motor vehicle (RMV) was the dependent variable, and the other predictors were represented as covariates. Following that, in the network structure section, the description, diagram and synaptic weights must be selected. In addition, the thick model summary, classification results and independent variables important analysis are required in the network performance path. It is possible to address which parameters have a significant role by comparing the result to the beta coefficient, level of significance, Nagelkerke R2 and hitting ratio in the logistic regression method. Development of right-turn motor vehicle in this study were implementing artificial neural network (ANN). Table 6 shows the processing summary of the model using 841 datasets. Training processing for AV Model involved 607 data meanwhile testing processing consisted of 234 data respectively. Area under curve (AUC) is a useful statistical summary of the network in the ANN AV model. The AUC in ANN AV Model is 0.947 which meant the model exhibited useful predictions. In the training process, correct prediction for ANN AV Model achieved 87% meanwhile testing process, received 89%. Furthermore, all model training time taken about 1 seconds.

Multilayer perceptron (MLP) is one of the common neural network models. MLP basic structure consist of one input layer, one or more hidden layer and one output layer. Each layer connected one or several nodes. Input layer has many nodes and represent of independent variables and similarly, with output layer has many nodes that represent dependent variables. Figure 9, shown the neural network structure for ANN AV Model. Figure 10, represent the probabilities of predicted pseudo and the result are shown in Table 6. The arrangement box illustrated the predicted pseudo-probability of the fitting classified cases of categories, “0” and “1”. The unfitting classified cases of both categories were observed under the cut point 0.5.

Attributes	ANN AV Model	
	Importance	Normalized Importance
Gap	0.427	100.00%
Rec	0.188	44.00%
AGc	0.153	36.00%
SMc	0.067	16.00%
Rider	0.053	13.00%
TV	0.042	10.00%
SCar	0.035	8.20%
Chlzation	0.034	8.00%
Total Sample	841	
Training/Testing	607/234	
Training Time	87%	
Testing (Correct Prediction)	89%	
Area Under the Curve	0.947	
Training Time	00:00.1	

Table 6: RMV at Urban Network

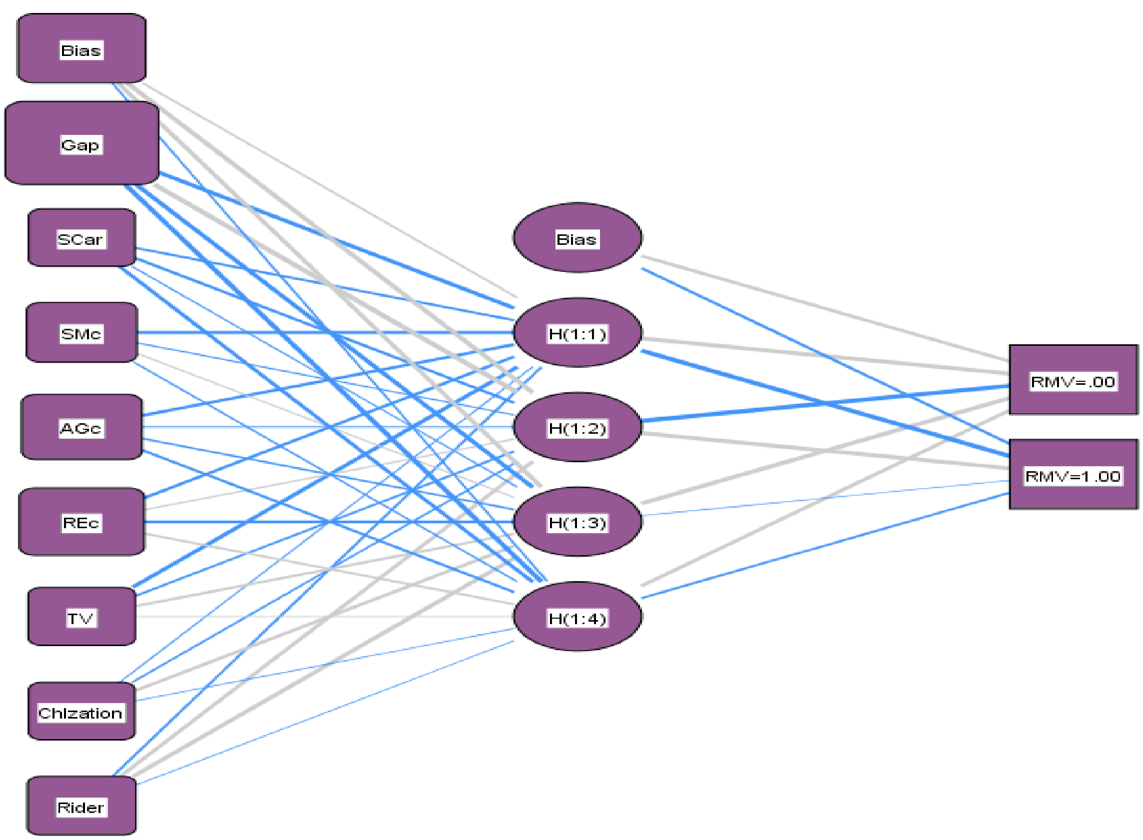

Figure 9: Artificial Neural Network AV Model

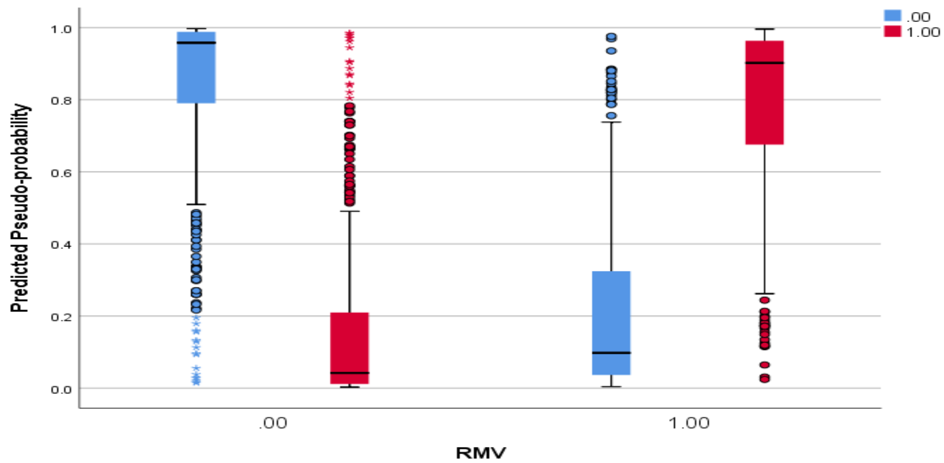

Figure 10: Predicted Pseudo-Probability

5. Discussion

Despite of collecting accident data from the authorities that involved many procedures, conflict study should be appropriate or alternative approach to identifying the blackspot location. Based on this research work, it is suggested that improvements to unsignalized intersections can be implemented based on identified blackspot locations. This approach involves analyzing traffic behavior, traffic conflict analysis, development RMV model and define critical gap at selected location aimed at enhancing safety and efficiency.

This study found the relation between traffic volume and number of conflicts influence the gap acceptance, which mean the higher the traffic volume and conflict the shorter the gap acceptance. In Equation 10, passenger car associate with traffic volume and rear-end conflict stated critical gap 2.83 seconds. In Equation 11, Motorcycle engages with traffic volume and angular conflict received critical gap 2.81 seconds. In Equation 12, all vehicle relates to traffic volume and rear-end conflict obtained critical gap 1.69 seconds.

RMV is Passenger car expose rear-end conflict and traffic volume appear to be the vulnerable type of vehicle with confidence level 90 % and obtain 2.83 critical gap by implementing Equation 10. Thus, appropriate safety measure necessarily to be implement. Although, safety infrastructure, enforcement and technology has been implemented. Without neglecting, traffic user mindset in road safety behaviours by providing education from early stage also need to be emphasize.

Rider and motorcycle received critical gap 4.74 seconds and 5.16 seconds respectively. Single rider or rider also determine the shorter critical gap among other type of vehicle. This scenario shows, single rider was the most vulnerable mode of transport as compare to motorcycle with pillion. Normally rider have high potential to engage with conflict, because the rider behaviour likely to manoeuvre fast, less heavy, and easily to swing [28-34].

6. Conclusion

This research reveals the eight predators in AV LRM model namely Gap, SCar, SMc, AGc, REc, Chlzation and Rider from LRM found highly significance with 99% confident level exclude traffic volume (TV) parameter obtained 95% confident level. meanwhile in ANN AV Model indicate all variables achieved more that 10% normalized important (NI) except for SCar and Chlzation. Which mean all the parameter were received 90% confident level if NI obtained higher than 10% [22]. Consequently. It concludes that both LRM and ANN ability to synchronize and similarity in term of understanding the output result.

Furthermore, the existing both angular conflict (AGc) and rear-end conflict (REc) at unsignalized intersection justifying RMV likely to accept shorter gap with 99% significance level as reveal in LRM AV Model. Both type of conflict necessarily to be handled carefully because it will trigger crash. Despite of traffic infrastructure like video camera, traffic signal and channelization, the application of intelligent vehicle establish IoT, V2V, IoV would be essential as active prevention from traffic conflict as well as accident.

This paper would like to highlight that angular conflict (AGc) associate with motorcycle, contribute factor for serious conflict with critical gap 2.81 seconds and possibility of accident might be happen. Meanwhile, rear-end conflict (REc) related RMVs were also initiate critical gap that can cause crash with critical gap 1.69 seconds. Thus, appropriate mitigation to avoid this event should be prioritize such as implementation of motorcycle lane and motorcycle zone at the unsignalized and signalized intersection. Beside that safety avoidance system such as advanced driver assistance system (ADAS) should be applied at all vehicle category. The outcomes from this study might provide critical view regarding traffic safety consent and useful input for autonomous vehicles in crash risk assessments.

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