Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 5
May 2023

A Study on Gap Acceptance between Vehicles and Pedestrians at Signalized and Unsignalized Zebra Crossings under the Hyderabad Metro Rail Route

Anukesh Chetlapally[1], Prof. M. Kumar[2]
[1]Ph. D (Full Time Student)
[2]Department of Civil Engineering
University College of Engineering
(Autonomous)
Osmania University, Hyderabad - 500 007

Abstract: The research is the pedestrian behavior of signalized and unsignalized behavior of Gap acceptance. Today's generation of pedestrian behavior the gap between the vehicle and pedestrian to find the insights of the speed head and time head between the gap acceptance to cross the road, while walking on the zebra with traffic signalized and unsignalized lights. The author is determined about the aim of this research identification and analyzing pedestrian behavior when the person is crossing behavior on the face detector, expressions, etc. The author researched the gap in acceptance of pedestrians when the person can cross the road, or not. They measured the pedestrian's behavior of signalized and unsignalized on the road. There is a chance to find out the distance between the vehicle and pedestrian with the traffic signalized is safer for them. But with unsignalized traffic signals were fewer chances to find and measure the distance between them, it is hazardous because sometimes, there are sudden happen accidents for pedestrians. The researcher has used the deep learning method as CNN, and the Open CV platform for the detection of pedestrian behavior of acceptancy of Gap. Here, the author has used real-time video recorder data for the analysis of the vehicles and pedestrians' distance between the gap acceptance. With the signalized and unsignalized behavior of pedestrians while gap acceptance of the time head and speed head will be analyzed the person will zebra cross the road or not for the acceptance of gap for the pedestrians while making a decision based on their destination to be reached.

1. Introduction

In the analysis of pedestrians' behavior of signalized and unsignalized of conditions of the road to cross the zebra lines. The person has to make a decision based on the traffic with the signal and without the signal for finding the traffic gaps for the pedestrians [1]. It is more complicated when on road traffic without the signal and the pedestrians have to cross the road. Based on the population on the road, the maximum number of traffic accidents are happening and people are died because of the Irregulating traffic lights with the signalized and unsignalized lights on the roads. The author is describing that based on the worldwide WHO organization described the traffic road lights of pedestrian fatalities [2]. In India, the situation is very difficult for zebra crossing for pedestrians. Sometimes making a not clear decision is complicated for pedestrians and vehicles will suddenly crash while crossing the road. The author is observing some of the time head and speed head between the vehicles-pedestrians on the zebra cross [3]. They used the measurement of the meters distance between them to cross the road or not. The features of the gap acceptance pedestrians and vehicles have to attempt the situations the time taken pedestrians attempts while crossing the zebra lines are measured as available, accepted, or rejected the gap between them [4].

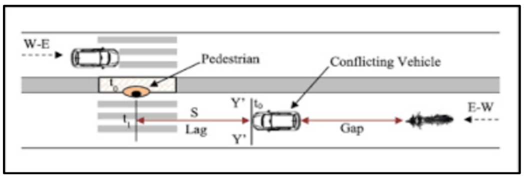

Figure *1.1* The Gap Acceptance of Pedestrian Behaviour Walk with the conflicted vehicle

The researcher is observing the impact of the features on the gap acceptance behavior of pedestrians. They are calculating the vehicle distance, vehicle speed, and time taken travel of the vehicle with the acceptance of the gap to cross the road [5]. The author has considered the signalized and unsignalized traffic lights when pedestrians are crossing the road, the research is based on the various features found such as Face detection, expression captures, Gender, number of pedestrians crossing the zebra, etc. [6]. The crossing behavior of pedestrians day by day increases the fatalities of people while crossing the zebra where there is no traffic controller.

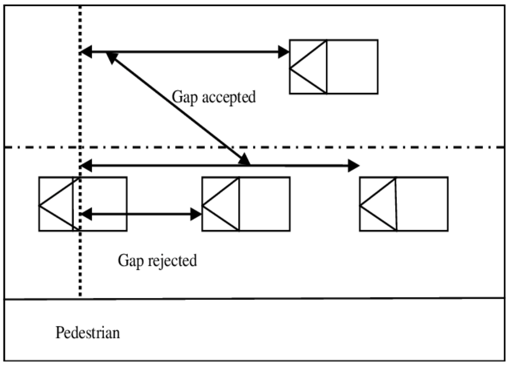

Figure *1.2* The Gap Acceptance or rejected of Pedestrian Walk with Vehicles

For example, assuming that the pedestrian on the zebra line with the crossing behavior of the signalized traffic lights is safer because there is the vehicle and pedestrian distance is about 10 feet and the speed is about 40kmph, then the pedestrian is safe. Then the unsignalized traffic lights of the pedestrian distance cannot be measured, and the vehicle of a person can come very fast then there is a higher level of chance of getting into a traffic accident with the major things on the road while the pedestrian is crossing the zebra [7]. If a maximum number of pedestrians are crossing the zebra while the maximum number of people with their vehicles are stopped at the traffic red signal to walk and reach their place. If un signalized traffic lights then the pedestrians may die on the road while crossing. Unsignalized of traffic lights are not accepting the gaps and can't able to find the Gaps while walking on the road [8]. The author has taken the metro line there is a lower chance of getting risk for the pedestrians to die. Near the metro line, it is very safer for zebra cross to reach their destination, because, there is a traffic controller and the policemen were observing each vehicle and pedestrian so that not to happen any accidents on the road [9]. On the road, pedestrians have an important thing to observe and identify the vehicles traveling with selected things of a gap to be crossed, and the speed and acceptance of the gap are important to cross the zebra line for the behavior of pedestrians. Pedestrian behavior on the road, when the pedestrian is crossing the road, they are evaluating the expressions of age, Gender, and facial detection of a person, and also carrying with their items of luggage when crossing the road making their structured decision of the zebra cross [10]. Then it is an easier way to find out whether the gap between the vehicle and pedestrians' behavior will reach safely and whether the pedestrian will cross the road or not.

2. Methodology

2.1 Distance between vehicle and pedestrian (space head)

The distance between a vehicle and a pedestrian is a crucial factor in ensuring road safety. Maintaining a safe distance is essential to prevent accidents and collisions. However, estimating this distance accurately can be challenging, especially in busy urban environments with heavy traffic [11]. In such situations, computer vision technologies such as Convolutional Neural Networks (CNN) can be used to estimate the distance between a vehicle and a pedestrian in both signalized and unsignalized terminals. CNN is a deep learning technique that can be used for object detection and recognition in real-time video streams. It uses multiple layers of artificial neural networks to extract features from images and classify objects. This makes it a useful tool for analyzing traffic and estimating the distance between a vehicle and a pedestrian. To estimate the distance between a vehicle and a pedestrian using CNN, the first step is to identify the objects in the video stream [12]. Object detection algorithms such as YOLO (You Only Look Once) or Faster R-CNN (Region-based Convolutional Neural Networks) can be used for this purpose. These algorithms use a combination of deep neural networks and machine learning (ML) techniques to detect and track objects in a video stream. Once the objects are detected, the next step is to estimate the distance between them. This is done using a technique called monocular depth estimation. Monocular depth estimation uses a single camera to estimate the distance of objects from the camera in signalized and unsignalized areas. It does this by calculating the depth from the camera using features extracted by CNN. The space head or the distance between the vehicle and the pedestrian can be estimated using the monocular depth estimation technique [13]. This is done by first estimating the depth of the pedestrian and the vehicle separately using CNN. Once the depth is estimated, the distance between the two objects can be calculated using basic trigonometry. The accuracy of the distance estimation depends on various factors, such as the quality of the video stream, lighting conditions, and the size and orientation of the objects being detected. To improve accuracy, techniques such as multi-camera systems, LiDAR (Light Detection and Ranging), and radar sensors can be used in conjunction with CNN-based distance estimation techniques. In addition to estimating the distance between vehicles and pedestrians, CNN can also be used to detect unsafe distances and alert drivers or pedestrians accordingly. For example, if the distance between a vehicle and a pedestrian fall below a certain threshold, an alarm can be activated to alert the driver [14]. Similarly, if a pedestrian is walking too close to the road or in a restricted area, an alert can be sent to the pedestrian or a nearby authority.

In conclusion, estimating the distance between a vehicle and a pedestrian is critical for ensuring road safety. CNN-based monocular depth estimation techniques can be used to accurately estimate this distance in real-time video streams. The accuracy of the estimation depends on various factors and additional sensors can be used to improve accuracy further. Using CNN for distance estimation can also help detect unsafe distances and alert drivers or pedestrians accordingly, enhancing road safety.

2.2 Distance measurements

Distance measurements are an important concept in deep learning as they are used to quantify the similarity between data points [15]. In machine learning, distance measurements are used for clustering, classification, and other applications that rely on similarity measures between data points. In deep learning, distance measurements are often used in neural network architectures such as Siamese networks, triplet networks, and contrastive loss functions. These architectures are designed to learn representations of data points that are close in distance to each other while being far away from other data points that are dissimilar [16]. This is useful for tasks such as image and face recognition, where the goal is to identify images or faces that are similar to each other and distinguish them from images or faces that are dissimilar. Some common distance measurements used in deep learning include the Euclidean distance, cosine distance, and Mahala Nobis distance. Euclidean distance is the most commonly used distance measurement in deep learning, as it is simple to compute and interpret [17]. Cosine distance is often used for text-based data and is less sensitive to the magnitude of the feature vectors. Mahala Nobis distance is used when the features are correlated, and it takes into account the covariance between features. The advantages of distance measurements make them an essential tool in many fields, providing accurate, efficient, and objective data that can be used to inform decision-making and advance scientific understanding.

2.2.1 Euclidean Distance

Euclidean distance is a popular distance metric it calculates the distance between the two points in a Euclidean space. The Euclidean distance formula uses the Pythagorean Theorem to calculate this distance [18]. The Pythagorean theorem is used to define a right-angled triangle, the sum of the square of the length of both sides will be equal to the hypotenuse. is equal to the. The algebraic notation is

$$a^2 + b^2 = c^2$$

To calculate the Euclidean distance between two points (a_1, a_2) and (b_1, b_2) in a 2-dimensional space

Steps:

Step 1: Subtract the coordinates of one point from the coordinates of the other point to get the difference.

$$ED_X = b_1 - a_1$$

$$ED_y = b_2 - a_2$$

Step 2: In the next step square each difference

$ED_x{}^2 = ED_x{}^{\wedge}\ 2$

$ED_y{}^2 = ED_y{}^{\wedge}\ 2$

Step 3: Add the squared differences

$$\text{Sum of Square} = ED_x{}^2 + ED_y{}^2$$

Step 4: Take the square root of the sum of the squared differences to get the Euclidean distance

$$\text{distance} = \text{sqrt(Sum of Squares)}$$

To calculate the Euclidean distance between two points in an n-dimensional space, we follow the same steps, but we subtract and square the differences for each dimension, and then sum the squared differences across all dimensions before taking the square root of the sum. Euclidean distance is a commonly used distance metric used by many people because it is very easy to understand. The Euclidean distance is a useful measure of distance or similarity between points in Euclidean space [19]. Its simplicity, ease of calculation, and wide applicability make it a valuable tool in many different fields.

2.2.2 Manhattan Distance

Manhattan Distance is used to find the distance between the two points present, the point usually will be in 2 dimensions. It is also known as city block distance or L1 distance as the points in the dataset move on the grid lines as they are moving on the grid of the city blocks present in Manhattan [20]. Manhattan distance can help find the distance between the two data points.

$$|x_1 - x_2| + |y_1 - y_2|$$

Where '|' represents the absolute value and it makes the value positive.

x_1, x_2 and y_1, y_2 represent the data points that involve the location of the pedestrian, and the second data point involve the location of the vehicle. By applying the Manhattan distance, the author can try to find the distance between the pedestrian and the vehicle. This is usually done with the application of OpenCV, and it will help in finding similar coordinates present in the image. By understanding the pattern of pedestrian behavior, and human behavior, insightful information from the images can be gathered and it helps in knowing the exact movement and speed of the vehicles. By observing the distance and speed of the vehicle and client the author can easily apply the time formula and get the time taken by the pedestrian to cross the vehicles or it will help find the time taken by the vehicle to cross the pedestrian. Speed is measured by multiplying distance and time. Thus, by finding the distance and speed, the author can easily gather information about the time.

2.2.3 Makowski Distance

Makowski Distance (M_D), is also known as fractional distance, and it is helped in finding the distance between the vehicle and pedestrians present on the road. This formula will help in developing the Manhattan distance and Euclidean distance. The value can be obtained by just changing the P value present in the formula [21]. The Makowski distance is a generalized form of the Makowski distance. It contains both Manhattan distance and Euclidean distance they have p as 1 and 2 respectively. In the Makowski distance, the degree of distance between two vectors is controlled by a parameter p, which can take on any non-negative real value. The formula for calculating the Makowski distance between two vectors x and y is:

$$\text{d (x, y)} = \left[\sum |x_i - y_i| \wedge p\right] \wedge \left(\frac{1}{p}\right)$$

By applying the above formula, the author can find any distance just by changing the value of the P. Application of CNN will help to analyze the behavioral pattern of the vehicles and pedestrians. However, some advantages help in handling the missing values present in the dataset and it helps in treating the outliers present in the dataset. Overall, the application of Makowski will help in understanding the distance between vehicles and pedestrians.

2.3 Pedestrian or Vehicle crossing time (Time head)

Pedestrian and vehicle crossing time also termed 'Time Head', is significant in road traffic management systems to improve the efficiency and safety of people on roads. Previously, time head was calculated using manual observations near traffic signals, which is considered a time-consuming task and is prone to errors. Currently, with the advent of Open CV and CNN, the calculation is automated quickly [22]. Open CV is a source of Computer Vision library under techniques of Deep Learning, providing tools and functions for image processing, object detection, and video analysis. It is widely used in the development of computer vision applications due to its simplicity and efficiency. While CNNs are a type of neural network that is particularly well-suited for image recognition tasks which are trained on huge datasets to learn the patterns and features relevant to the task at hand.

The collection of data needs to be taken place to find the time head using Open CV and CNN, and the data may be on video footage from cameras mounted on traffic lights or poles. Next, the data is processed using Open CV to extract frames and detect objects of interest such as pedestrians and vehicles. OpenCV functions can be used to accomplish this, including background subtraction, object tracking, and image segmentation. Once the objects of interest are identified CNNs are used to classify them into pedestrian or vehicle categories. But prior CNN must be trained on a dataset of labeled images, and they must be of wide varieties including lighting conditions, weather conditions, and viewpoints. Then CNN learns to recognize patterns and features in the images that are specific to pedestrians or vehicles, such as the shape, size, and motion of the objects [23]. Once the CNN is trained, it can be used to classify the objects in the video frames into pedestrian or vehicle categories and later the moments of these objects can be tracked over time using Open CV. It determines when a pedestrian or vehicle enters and exits the crosswalk, and how long it takes for them to cross. Finally, by analyzing all the data, the Time Head can be calculated for each pedestrian or vehicle which can be used to optimize traffic signal timings and improve safety on roads.

Challenges are also present in calculating Time Head using Open CV and CNN and one of the major challenges include object detection. If is affected by the factors such as weather conditions, lighting conditions i.e., day or night, and occlusion, etc. To address these issues, multiple techniques can be utilized, and they involve image enhancement, multi-object tracking, and adaptive thresholding. Enhanced imaging is used for providing images with better visual quality. Multi-object tracking using DL involves detecting and tracking multiple objects simultaneously in video sequences, which can be challenging due to occlusions, motion blur, and object appearance changes [24]. Adaptive thresholding improves image segmentation by adapting the threshold values to local image regions. Another challenge is dataset bias, it occurs if the training set isn't representing the real-world data. To mitigate this, techniques such as data augmentation, transfer learning, and cross-validation are used. Data augmentation artificially increases the size of a dataset by applying transformations to the original data. Transfer learning involves using a pre-trained model as a starting point for a new task and fine-tuning the model on new data [25]. Lastly, Cross-validation involves dividing a dataset into multiple subsets for training and testing, to evaluate the performance of a model on unseen data.

2.4 Speed measurements

$$\text{Speed} = \frac{\text{Distance}}{\text{Time}}$$

To measure the speed there are several units like kilometers per hour ($\frac{\text{km}}{\text{h}}$), miles per hour (mph), meters per second ($\frac{\text{m}}{\text{s}}$), and feet per second ($\frac{\text{ft}}{\text{s}}$),). For measuring the speed of a given object, it is needed to measure the distance it covered and how much time it takes to cover that particular distance. In today's modern world, the speed measurement of vehicles and pedestrians is becoming increasingly important. To avoid traffic accidents and reduce them [26]. With the rapid progresses in technology, new techniques are emerging to measure the speed of objects and track their movements in real-time. One such technology is Convolutional Neural Networks (CNN), which have revolutionized the field of computer vision [27]. CNN is a type of artificial neural network that has proven to be highly effective in image recognition, object detection, and object tracking. It is widely used in various applications, such as surveillance, self-driving cars, and robotics. CNN is particularly useful in measuring the speed of objects, such as pedestrians and vehicles. To measure the speed of objects using CNN, object tracking algorithms can be used. These algorithms use various methods to track the movement of objects in a video sequence [28]. One popular tracking algorithm is the Kalman filter, which is widely used in robotics and aerospace applications. It uses a mathematical model to estimate the position and velocity of the object being tracked. Another tracking algorithm that is commonly used in CNN is the particle filter. It is a probabilistic algorithm that can track multiple objects simultaneously. The particle filter uses a set of random samples or particles to estimate the position and velocity of the object being tracked. The correlation filter is another popular tracking algorithm used in CNN [29]. It works by creating a template of the object being tracked and then correlating it with the current image frame. This enables it to track the object's position and velocity accurately. Once the object's position and velocity are estimated using these tracking algorithms, its behavior can be analyzed to identify patterns and potential risks. For example, if a pedestrian is walking too slowly or erratically, it could indicate that they are impaired or distracted, and measures can be taken to prevent accidents. Similarly, if a vehicle is moving too fast or violates traffic rules, it could be flagged for further investigation or intervention. The speed measurement data can also be used to optimize traffic flow and improve road safety [30]. In addition to tracking objects, CNN can also be used to measure the speed of objects directly. This is done using optical flow, which is a technique that measures the relative motion between two frames of a video sequence. Optical flow is widely used in video analysis and can provide accurate speed measurements of objects in motion. To summarize, speed measurement in CNN has several applications in today's world. It can be used to track the movements of pedestrians and vehicles, analyze their behavior, and optimize traffic flow [31]. Object tracking algorithms such as the Kalman filter, particle filter, and correlation filter can be used to estimate the position and velocity of objects accurately. Optical flow can be used to measure the speed of objects directly. These techniques can provide valuable insights into the behavior of pedestrians and vehicles in various settings, which can be used to enhance safety and efficiency [32].

3. Result and Analysis

Accepting a gap is when the driver of the chosen vehicle joins with the moving traffic from the location of the vehicle at the roundabout's entrance as soon as the space is wide enough to prevent collisions or serious conflicts. In this project proposal, the author will analyze the disparity in acceptance at both signaled and unsignalized places.

A few things are required for the author to finish this project. a top-notch camera for capturing the movements of people walking. This technology can be applied when pedestrians are detected. The system accurately recognizes the pedestrian. An endless number of pedestrians could be recognized concurrently. For efficient detection, four persons were used. This is more than just a simple count of pedestrians. There are 80 distinct, foreseeable assignments in the class. This author used the COCO dataset of web pages for prediction purposes. The author must first use the pre-defined method to get the class ids to count pedestrians and track object ids. This feature yields precise outcomes in projects of this nature. The results analysis was successfully performed.

3.1 Pedestrian behavior on Zebra Line

Here, the author displays the output using one of the top libraries, OpenCV. The reader can grasp the scenario of the pedestrian who is a bit distant from the endpoint and is traveling in the same direction to cross the road by looking at Fig. 4.1, which depicts a pedestrian walking on a zebra line. One message at the top of the rectangle asks if there is a safe zone between people and cars and if the distance is great, it indicates one. This Fig. 4.1 shows two things: whether a pedestrian is in the safe zone and how many feet they are away from the endpoint. The rectangle box displays a green color indicating if the pedestrian is crossing a zebra and a pink color indicating if they are both. The reader can quickly determine whether the characters are walking on zebras with these kinds of variances.

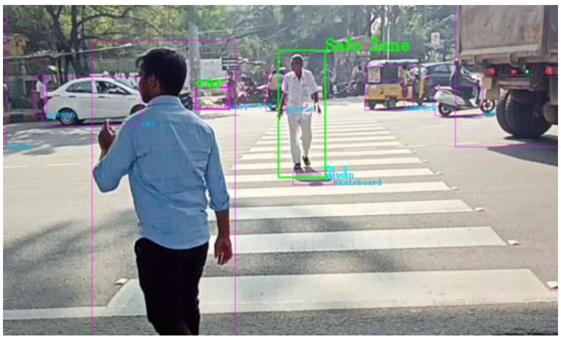

Figure *3.1* Behaviour of the pedestrian at signalized area

Fig. 4.2 shows some important things. One is the separation between the pedestrian and the zebra line's terminus in signalized areas. The suggested project's second key criterion is whether or not pedestrians are in a safe zone. The person standing in the center of the road and the space between her and the zebra line's endpoint in the accompanying illustration both serve as warning signs that a pedestrian may be in danger of being involved in an accident.

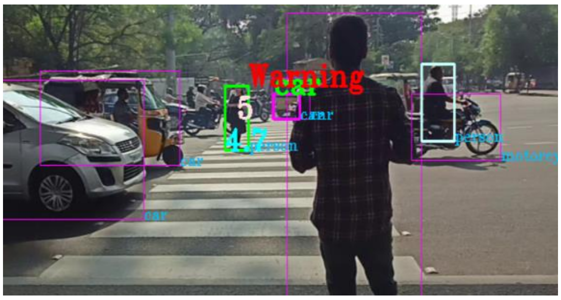

Figure *3.2* Gap between endpoint and pedestrian and warning alert

3.2 Pedestrian behaviour in signalized

Here, the author will go over the dangers of zebra crossings in no-signal areas. There is a danger of an accident if the pedestrian is crossing in a zone with no signals and no zebras. The majority of Indian highways lack proper zebra crossings which people are supposed to pass while obeying the law. The reader may see in this Fig. 4.3 how many people are using the zebra queue to cross the street. A warning alert is displayed here where a small group of individuals are in a safe area. Most of the pedestrians are not able to cross the road properly.

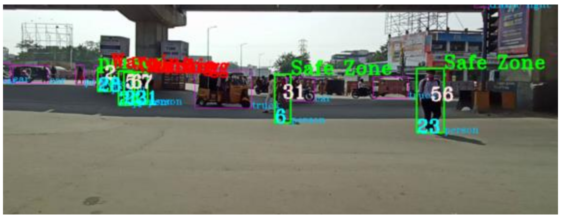

Figure *3.3* Behaviour of the pedestrian unsignalized area

3.3 Limitations and feature scope of this Project

Spatial transferability is the results' biggest drawback. It is stated that road users' behaviour is directly tied to the local culture, as is the case with the majority of comparable studies on this subject. The validity of such research findings is typically restricted to a certain region with a similar transportation culture. For instance, the majority of simulation models currently in use were created using data gathered in developed countries and are not suitable for use in developing countries, where mixed traffic is more prevalent. The model is at least valid at a city-wide level because it makes intuitive sense that residents of the same area or city share the same culture. However, it is still necessary to examine the model's quantitative transferability, perhaps by validating it using data from some other sites in the city. If the model's validity reduces dramatically, the researchers need to go through the calibration process to alter its parameters or logic, or even to design new models.

3.4 Data Visualization and Model Obtained Result

Some of the important observations are applied in this section and gives the different model performance. For creating the model and representing the data information related to space head and time head here the author collected the data information from the live streaming data through Open CV and stored this data information in a tabular format then apply these things.

3.4.1 Time head counting

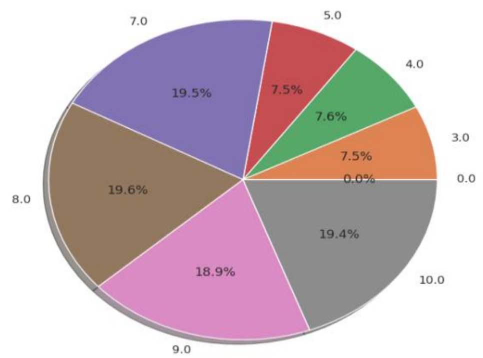

Figure 3.4 Showing distribution of time head data

Here it can be seen in Fig. 3.4 that the highest delay is observed in 7,8,9 and 10 seconds in both signalized and unsignalized terminals due to various reasons as described in previous sections. And less delay is observed at 3,4 and 5 seconds. But the important thing is observed that there is no person who crossed the road in time and it represents 0 percent of people are delayed with zero seconds means no one crossed in time everyone is delayed.

3.4.2 Space head

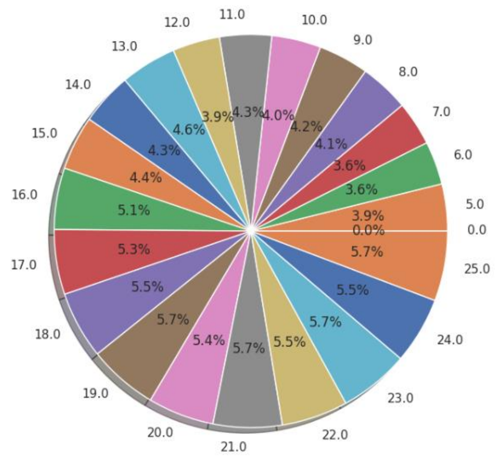

Figure 3.5 represents the delay for the space head

Fig. 3.5 represents the delay related to the space head and it can be seen that almost every distance of the space head is almost equivalent distribution delay in both signalized and unsignalized terminals.

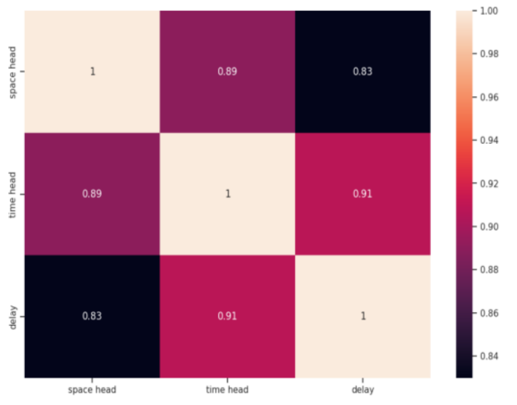

Figure 3.6 Correlation between all attributes

In Fig. 3.6 it can be seen that all the attributes are highly correlated to each other which means both the time head and space head are strongly correlated and represent the same thing in the dataset. If considered with target column delay it is also observed that both independent columns are strongly related to the target column which means they are important in model creation.

3.4.3 Model performance analysis

As the author tries to predict the delay time so it comes under the regression problem and that's why the author applies five different regression models in that case and these are DT regressor, lasso regressor, Linear regressor, Regressor, SVC, and ridge regressor. After applying all the model performances are given below one by one.

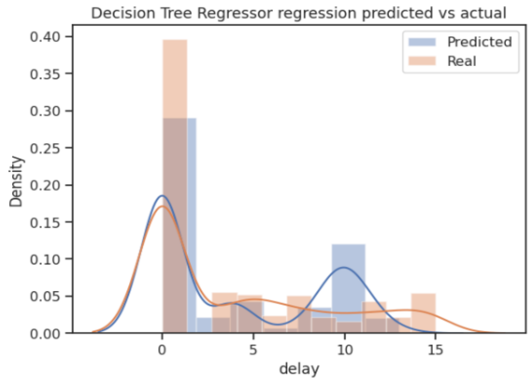

Figure 3.7 DT regressor actual vs predicted comparison graph

It can be seen in Fig. 3.7 that the author created a comparison graph of the DT model and it is observed that there are some differences between the actual and predicted values. That means the model has not learned all the hidden patterns in an appropriate way.

	Actual	Predicted
302	7.0	9.500000
1276	4.0	4.222222
190	8.0	11.125000
323	15.0	9.285714
427	0.0	0.000000

Table 1 Shows actual and predicted table values

Here the author shows the actual vs predicted values in a tabular format and it is observed that the values are not exactly equal by almost near values and as shown in Table 1.

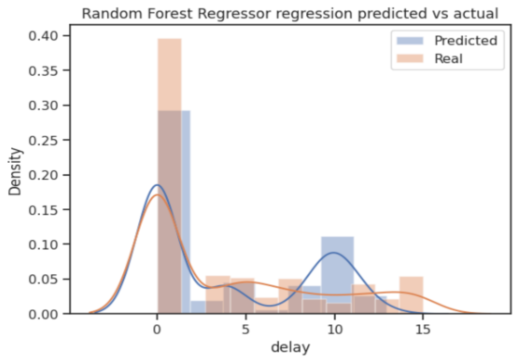

Figure 3.8 RF model actual vs predicted graph

Fig. 3.8 represents the comparison between the actual vs predicted RF model and it can be seen that it is almost similar to the DT model comparison graph. That means it is also not able to learn all the patterns correctly and not able to give a more accurate prediction.

	Actual	Predicted
302	7.0	9.470276
1276	4.0	4.222577
190	8.0	11.201948
232	15.0	9.208589
472	0.0	0.000000

Table 2 RF actual vs predicted values table

Table 2 represents that there are some values that are very close to the actual values and some are quite far from the actual values which means the models should predict in a more accurate way.

Model	RMSE	MSE	MAE	MAPE	R2
LinearRegression	2.09	4.36	1.16	11280811374544.60	0.83
LassoRegression	2.12	4.50	1.26	466494579176937.69	0.82
RidgeRegression	2.09	4.36	1.16	11456230626096.61	0.83

Figure 3.9 Linear, Lasso, and Ridge performance analysis

There is a comparison table of three algorithms model performance is given and it is observed that there are not too many differences between these algorithms and all perform 83 percent except Lasso. Lasso performs 82 percent of R-Square and it can be shown in Fig. 3.9.

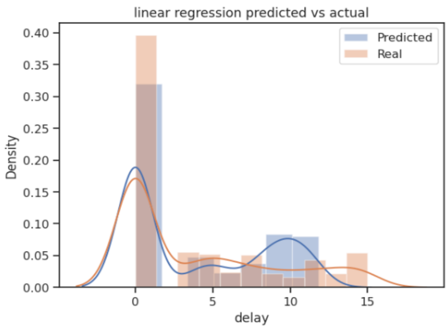

Figure 3.10 LR model actual vs predicted

After applying the LR model in this dataset the author gets almost similar predictions to actual values but still, there are some gaps between the values of actual vs prediction.

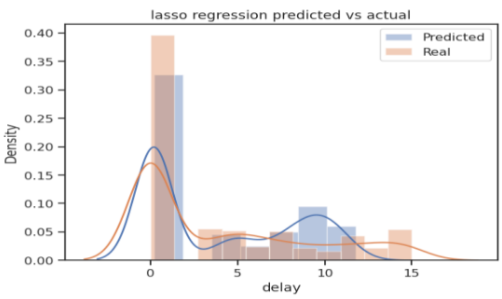

Figure 3.11 Lasso model actual vs predicted graph

It seems to be similar to the previous LR model seeing Fig. 3.11. That means this one also has almost similar prediction power to LR.

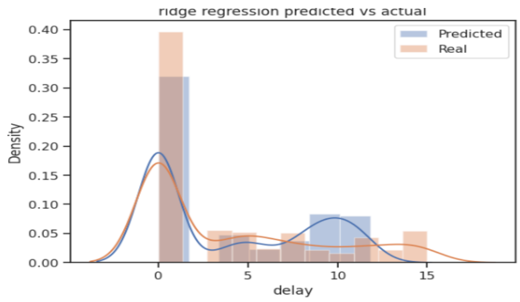

Figure 3.12 Ridge model actual vs predicted graph

After applying the Ridge algorithms, the author gets the same output as the LR and lasso models. There is not to difference between them and it can be seen in Fig. 3.12.

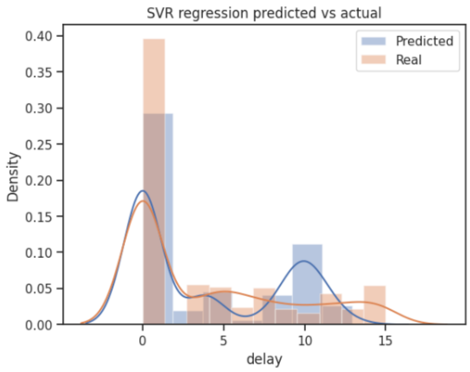

Figure 3.13 SVC model actual vs predicted graph

After applying the SVC model also the author was not able to get any differences between all these models that means author get similar predicted values same as remaining algorithm.

	Actual	Predicted
302	7.0	9.470276
1276	4.0	4.222577
190	8.0	11.201948
232	15.0	9.208589
472	0.0	0.000000

Table 3 SVC model comparison table of actual vs predicted

Here also observed that there are almost similar to the predicted value and it is shown in table 3. So, that means there is no too much significant difference between all the models, they all are almost the same.

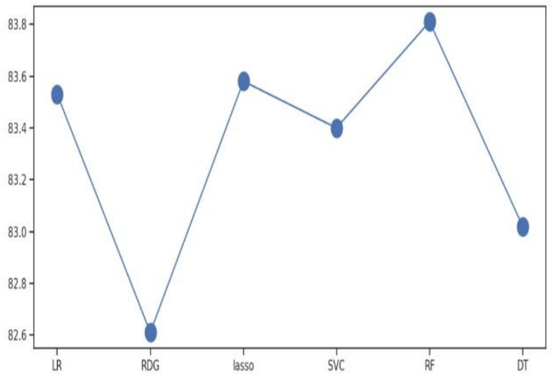

Figure 3.14 Comparison graph of all model performance

It can be seen in Fig. 3.14 that all the model performances are almost the same but still, there are some significant differences in performance in decimal points and based on that the RF model gives the best performance in this dataset with an R-Square of 83.8 percent. That's why the author finalized the RF model for this problem statement.

4. Conclusion

Based on picture pre-processing observations from actual PVI settings, this article used deep learning approaches to analyze and simulate the pedestrians' gap acceptance behavior when they jaywalk outside of crossing facilities in signalized and unsignalized terminals. Three indicators including near-side traffic gap time, pedestrian's age category, and number of pedestrians in a crossing group, out of six proposed ones, are deemed to be relevant enough to be included in all objectives. The initial results with the logit model are promising when evaluated in combination with its simplicity and accuracy.

References

[1] Zhu, D., Sze, N.N. and Bai, L., 2021. Roles of personal and environmental factors in the red light running propensity of pedestrian: Case study at the urban crosswalks. Transportation research part F: traffic psychology and behaviour, 76, pp.47-58.

[2] Mohammed, A.A., Ambak, K., Mosa, A.M. and Syamsunur, D., 2019. A review of traffic accidents and related practices worldwide. The Open Transportation Journal, 13(1).

[3] Dey, D., Walker, F., Martens, M. and Terken, J., 2019, September. Gaze patterns in pedestrian interaction with vehicles: Towards effective design of external human-machine interfaces for automated vehicles. In Proceedings of the 11th international conference on automotive user interfaces and interactive vehicular applications (pp. 369-378).

[4] Saxena, A. and Yadav, A.K., 2023. Clustering pedestrians' perceptions towards road infrastructure and traffic characteristics. International journal of injury control and safety promotion, 30(1), pp.68-78.

[5] Zafri, N.M., Sultana, R., Himal, M.R.H. and Tabassum, T., 2020. Factors influencing pedestrians' decision to cross the road by risky rolling gap crossing strategy at intersections in Dhaka, Bangladesh. Accident Analysis & Prevention, 142, p.105564.

[6] Mukherjee, D. and Mitra, S., 2019. A comparative study of safe and unsafe signalized intersections from the view point of pedestrian behavior and perception. Accident Analysis & Prevention, 132, p.105218.

[7] Ali, Y., Haque, M.M., Zheng, Z. and Afghari, A.P., 2022. A Bayesian correlated grouped random parameters duration model with heterogeneity in the means for understanding braking behaviour in a connected environment. Analytic methods in accident research, 35, p.100221.

[8] Rasouli, A. and Kotseruba, I., 2022, June. Intend-Wait-Cross: Towards Modeling Realistic Pedestrian Crossing Behavior. In 2022 IEEE Intelligent Vehicles Symposium (IV) (pp. 83-90). IEEE.

[9] Arellana, J., Fernández, S., Figueroa, M. and Cantillo, V., 2022. Analyzing pedestrian behavior when crossing urban roads by combining RP and SP data. Transportation research part F: traffic psychology and behaviour, 85, pp.259-275.

[10] Jahandideh, Z., Mirbaha, B. and Rassafi, A.A., 2019, March. Identifying factors affecting pedestrians' crossing decisions at intersections in Iran. In Proceedings of the Institution of Civil Engineers-Municipal Engineer (Vol. 172, No. 1, pp. 26-36). Thomas Telford Ltd.

[11] Jamal, A., Rahman, M.T., Al-Ahmadi, H.M. and Mansoor, U., 2020. The dilemma of road safety in the eastern province of Saudi Arabia: Consequences and prevention strategies. International journal of environmental research and public health, 17(1), p.157.

[12] Kim, S.J., Nam, J.Y. and Ko, B.C., 2018. Online tracker optimization for multi-pedestrian tracking using a moving vehicle camera. IEEE Access, 6, pp.48675-48687.

[13] Klingner, M., Termöhlen, J.A., Mikolajczyk, J. and Fingscheidt, T., 2020. Self-supervised monocular depth estimation: Solving the dynamic object problem by semantic guidance. In Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XX 16 (pp. 582-600). Springer International Publishing.

[14] Wang, X., Li, J., Zhang, C. and Qiu, T.Z., 2019. Active warning system for highway-rail grade crossings

using connected vehicle technologies. Journal of advanced transportation, 2019, pp.1-11.

[15] Botchkarev, A., 2019. A new typology design of performance metrics to measure errors in machine learning regression algorithms. Interdisciplinary Journal of Information, Knowledge, and Management, 14, pp.045-076.

[16] Frosst, N., Papernot, N. and Hinton, G., 2019, May. Analyzing and improving representations with the soft nearest neighbor loss. In International conference on machine learning (pp. 2012-2020). PMLR.

[17] Yan, Q., Wang, M., Huang, W., Luo, X. and Yu, F.R., 2019. Automatically synthesizing DoS attack traces using generative adversarial networks. International journal of machine learning and cybernetics, 10(12), pp.3387-3396.

[18] Suwanda, R., Syahputra, Z. and Zamzami, E.M., 2020, June. Analysis of euclidean distance and manhattan distance in the K-means algorithm for variations number of centroid K. In Journal of Physics: Conference Series (Vol. 1566, No. 1, p. 012058). IOP Publishing.

[19] Ikotun, A.M., Ezugwu, A.E., Abualigah, L., Abuhaija, B. and Heming, J., 2022. K-means Clustering Algorithms: A Comprehensive Review, Variants Analysis, and Advances in the Era of Big Data. Information Sciences.

[20] Faisal, M. and Zamzami, E.M., 2020, June. Comparative analysis of inter-centroid K-Means performance using euclidean distance, canberra distance and manhattan distance. In Journal of Physics: Conference Series (Vol. 1566, No. 1, p. 012112). IOP Publishing.

[21] Liu, Z.N., Yu, X.Y., Jia, L.F., Wang, Y.S., Song, Y.C. and Meng, H.D., 2021. The influence of distance weight on the inverse distance weighted method for ore-grade estimation. Scientific Reports, 11(1), p.2689.

[22] Dow, C.R., Ngo, H.H., Lee, L.H., Lai, P.Y., Wang, K.C. and Bui, V.T., 2020. A crosswalk pedestrian recognition system by using deep learning and zebra-crossing recognition techniques. Software: Practice and Experience, 50(5), pp.630-644.

[23] Brunetti, A., Buongiorno, D., Trotta, G.F. and Bevilacqua, V., 2018. Computer vision and deep learning techniques for pedestrian detection and tracking: A survey. Neurocomputing, 300, pp.17-33.

[24] Ka, D., Lee, D., Kim, S. and Yeo, H., 2019. Study on the framework of intersection pedestrian collision warning system considering pedestrian characteristics. Transportation research record, 2673(5), pp.747-758.

[25] Li, X., Grandvalet, Y., Davoine, F., Cheng, J., Cui, Y., Zhang, H., Belongie, S., Tsai, Y.H. and Yang, M.H., 2020. Transfer learning in computer vision tasks: Remember where you come from. Image and Vision Computing, 93, p.103853.

[26] Maruhn, P., Dietrich, A., Prasch, L. and Schneider, S., 2020, March. Analyzing pedestrian behavior in augmented reality—proof of concept. In 2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR) (pp. 313-321). IEEE.

[27] Alam, M., Samad, M.D., Vidyaratne, L., Glandon, A. and Iftekharuddin, K.M., 2020. Survey on deep neural networks in speech and vision systems. Neurocomputing, 417, pp.302-321.

[28] Sudha, D. and Priyadarshini, J., 2020. An intelligent multiple vehicle detection and tracking using modified vibe algorithm and deep learning algorithm. Soft Computing, 24, pp.17417-17429.

[29] Abbasi, M. and Khosravi, M.R., 2020. A robust and accurate particle filter-based pupil detection method for big datasets of eye video. Journal of Grid Computing, 18(2), pp.305-325.

[30] Thakur, A. and Malekian, R., 2019. Internet of vehicles communication technologies for traffic management and road safety applications. Wireless Personal Communications, 109, pp.31-49.

[31] Zhu, J., Chen, S., Tu, W. and Sun, K., 2019. Tracking and simulating pedestrian movements at intersections using unmanned aerial vehicles. Remote Sensing, 11(8), p.925.

[32] Zhao, J., Xu, H., Liu, H., Wu, J., Zheng, Y. and Wu, D., 2019. Detection and tracking of pedestrians and vehicles using roadside LiDAR sensors. Transportation research part C: emerging technologies, 100, pp.68-87.