Proceedings of the 11th World Congress on Electrical Engineering and Computer Systems and Sciences (EECSS'25)
Paris, France - August, 2025
Paper No. MVML 107
DOI: 10.11159/mvml25.107

Nighttime Detection of Illegal Crossing by Pedestrians and Pedestrian Lane Obstruction by Vehicles through Effective Deep Learning Model

Abigail Manoguid[1], John Paul Tomas[2]
[1]Mapua University
1191 Pablo Ocampo Sr. Ext, Makati, Metro Manila, Philippines
almanoguid@mymail.mapua.edu.ph; jpqtomas@mapua.edu.ph
[2]Mapua University
1191 Pablo Ocampo Sr. Ext, Makati, Metro Manila, Philippines

Abstract **-** Most object detection methods can perform well in detecting pedestrians and vehicles in the daytime; however, the task becomes more difficult at night. This study measures the effectiveness of a modified Faster RCNN with a ResNet34 backbone, Squeeze and Excitation Network, Feature Pyramid Network, and Contrast Limited Adaptive Histogram Equalizer in detecting pedestrians and vehicles, and violations committed on the pedestrian lane in the Philippines setting. The results of this study show that the model showed an improvement of 15.37% from the unmodified Faster RCNN architecture and 1.31% from the Faster RCNN with a ResNet50 backbone and Feature Pyramid Network in the mean average precision metric. With the current modifications to the architecture, the model could confidently detect vehicles but had difficulty detecting pedestrians.

Keywords**:** Pedestrian detection, vehicular detection, nighttime detection, Faster RCNN, ResNet34, Squeeze and Excitation Network, Contrast Limited Adaptive Histogram Equalizer, K-Fold Cross Validation

1. Introduction

The Philippines is a rapidly urbanizing country, and so, it faces challenges regarding pedestrian safety and traffic management. With the increasing number of vehicles on the roads and the population of the cities, concerns about pedestrians and crossing roads have been a growing talking point among the population. Two critical issues exacerbate the risks faced by pedestrians: illegal pedestrian crossings and pedestrian lane obstructions caused by vehicles [1]. Illegal crossings occur when pedestrians cross the road at non-designated areas, while pedestrian lane obstructions occur when vehicles occupy and block the designated areas for crossing, forcing pedestrians to walk on roadways, both exposing the pedestrian to harm.

Both pedestrian detection and vehicular detection play a significant role in road safety and traffic management. Before the introduction of object detection systems in this area, traditional pedestrian detection methods were used [4]. These methods, however, do have weaker structures and have lower accuracy and overall performance [4, 5]. Nowadays, many studies have proposed the automation of pedestrian and vehicular detection using object detection systems as a means for better traffic monitoring to enhance pedestrian safety [6]. These pedestrian and vehicular detection technologies are used in intelligent video surveillance, artificial intelligent systems, and more [4, 6]. However, most of the object detection systems have been unable to achieve the benchmarks set for vehicle detection [2] and pedestrian detection [3].

Many previously conducted studies have encountered and tried to alleviate two common challenges: occlusions and object scale variations [2, 13]. However, in many of these studies, the proposed models struggled to maintain their performance when it comes to nighttime detection. The researcher used this opportunity to conduct a study on nighttime detection of illegally crossing pedestrians and obstructing vehicles in the Philippines setting. Adopting the information from other studies, the researcher used ResNet34 + FPN, as well as a feature attention module and a transformation module to further improve the accuracy of their proposed model. To increase the model's accuracy in detecting smaller and occluded objects, the researcher used the Squeeze and Excitation Network as their feature attention module [18].

2. Review of Related Literature

2.1. Pedestrian and Vehicular Detection

Many pedestrian and vehicular studies have encountered issues that negatively affected the results of their work. This is due to the common challenges faced by both pedestrian and vehicular detection: occlusions, small object detection, and light variations [2, 3, 6, 14, 16].

In the study conducted by Sangeeth Mathew John, Fathima Abdul Kareem, Sachin Gee Paul, Abdul Gafur M, Saeed Al Mansoori, and Alavikunhu Panthakkan (2023) on vehicle detection, they found that one of the problems was in regard to false positives and false negatives. The false positives were attributed to the model's inability to differentiate vehicles from other objects with similar features such as the trees and the buildings. The false negatives were attributed to the complexity of the images, which included occlusions, shadows, and variations in the lighting and weather conditions.

The review conducted by Yangzhi Wang, Ruibin Zou, Yilu Chen, and Zhenxing Gao (2023) talks about the many different methods of vehicle detection. It was found that two-stage detection models have higher accuracies than one-stage models and an example of a commonly used two-stage detection model is the Faster RCNN.

In the study done by Guo Xiaoying, Liu Qiaoling, Qin Zhikang, and Xu Yan (2021), a vehicle detection system was proposed utilizing an improved SSD algorithm to solve the low accuracy results and false negatives that the unmodified SSD algorithm encounters. The proposed system makes use of a ResNet50-based SSD network for multi-scale feature extraction, a Feature Fusion Model for deep and shallow information fusion, and a Squeeze-and-Excitation (SE) block for dynamically adjusting the features of each channel.

On the other hand, according to S. Devi, R. Dayana, and P. Malarvezhi (2023), it was observable that the unmodified Faster RCNN architecture had missed identification because of darker parts brought on by changes in lighting and viewpoint, as well as overlapped pedestrian occlusion.

2.2. Nighttime Detection

Although most object detection methods were able to perform reasonably well in detecting pedestrians and vehicles in the daytime, the task becomes more difficult at night. In the study conducted by Gang Li, Shanshan Zhang and Jian Yang (2021), it was found that it was more difficult for CNN-based detectors to detect pedestrians at night, whose contrast is significantly lower than that of daytime. Dark pedestrians trigger low feature responses at some parts and can only provide weak visual cues. Compared to daytime images, it is more difficult to classify pedestrians from background clutter at nighttime, due to the low contrast, reduced color information, and image noise, induced by poor and inhomogeneous illumination. Studies conducted on nighttime detection transformed the features of their dataset to better improve the learning of their models [15, 16].

In a study conducted by Gang Li, Shanshan Zhang and Jian Yang, their approach was to enforce the features from lower illumination than the features from better illumination. Another study that focuses on nighttime detection used encoders to retrieve weaker signals from nighttime images [15].

Another nighttime detection study had taken a different approach, focusing on enhancing the illumination of nighttime images [19]. They utilized an image enhancement algorithm known as the Contrast Limited Adaptive Histogram Equalization, also known as CLAHE.

2.3. Faster RCNN

The Faster RCNN architecture is commonly used in both pedestrian and vehicular detection [6, 14, 15, 16]. In this architecture, the core idea is to use the RPN to screen out the regions of interest and then train on this basis; the extracted features are then used to classify and regression the recommended regions. This method is often difficult for identifying small-scale pedestrians in complex scenes, making pedestrian detection more difficult [14]. Different studies have shown that modifications can improve the performance of this algorithm and lead to respectable results.

An example of this is a proposed improved Faster RCNN that incorporated the Feature Pyramid Network, it had high results and was capable of detecting smaller objects in different lightings [12]. In this study, the authors compared the performance of two modified Faster RCNN models, one had a ResNet34 backbone while the other had a ResNet50 backbone.

The ResNet34 + FPN model performed better than ResNet50 + FPN model, with accuracies of 91.23% and 72% respectively, in daytime pedestrian detection [12].

A study proposed a modified Faster R-CNN, implementing the Shuffle Attention Mechanism, Transformer Module, and Feature Pyramid Network, for night-time pedestrian detection [15]. Although the proposed model's performance has significantly improved when compared to the default Faster R-CNN, it still had a high miss rate when detecting small and occluded objects, 21.26 and 34.32 respectively, despite its miss rate for reasonably sized objects is 8.24.

Sweta Panigrahi and U.S.N. Raju (2021) proposed a Faster R-CNN system for pedestrian detection, which they called DCResNet. The proposed method achieves good performance on both datasets, with an average precision of 89.4% on Caltech and 81.5% on KITTI.

In the study conducted by Xiaoqiang Shao, Jinyang Wei, Defeng Guo, Runyang Zheng, Xinchao Nie, Guowei Wang, and Yu Zhao (2021), the k-means clustering algorithm was utilized to extract the initial pedestrian area, using RPN to quickly generate the recommended candidate regions. The detection of small-scale pedestrians is improved through the method of high- and low-level feature fusion and the OHEM algorithm.

Proposing another improved Faster RCNN model, Chunling Yang and Dong Qiu (2022) utilized the SENet (Squeeze and Excitation Network) and FPN as an improvement to the feature extraction network. SENet improved the model's learning by emphasizing more informative features and suppressing useless ones Qiangbo Zhang, Yunxiang Liu, Yu Zhang, Ming Zong, and Jianlin Zhu (2023) also used SENet in their study. Their proposed model could identify occluded pedestrians by assigning greater weights to the features of non-occluded targets.

3. Methodology

3.1. Conceptual Framework

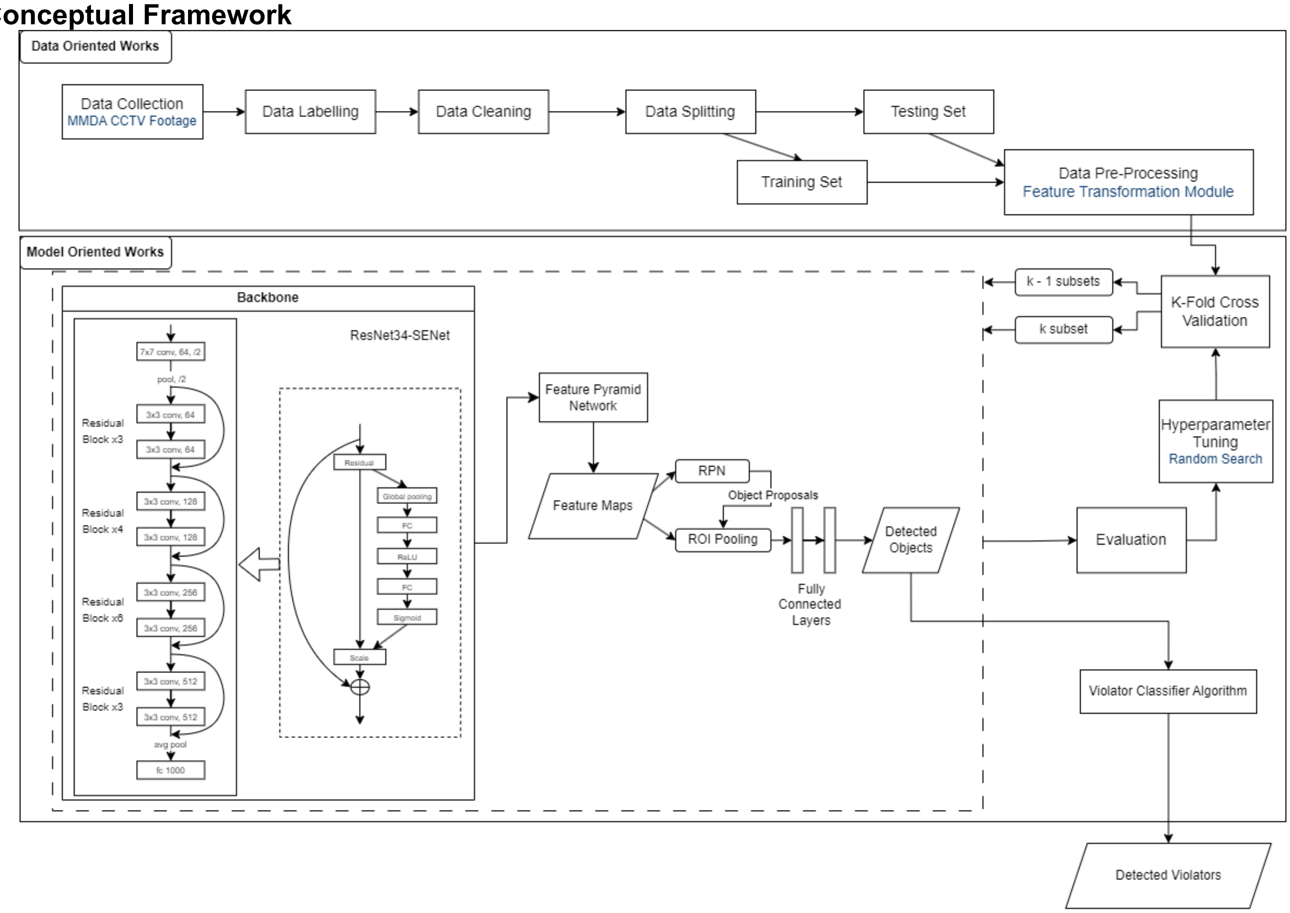

Fig 1: Proposed Framework

3.2. Data Collection

The researcher gathered the dataset from pre-recorded nighttime CCTV video footage of the MIA-Quirino Intersection, located at Quirino Avenue, Pasay City, under NAIA expressway. The location was chosen for its high concentration of pedestrians and crossing vehicles. The footage was gathered from the MMDA, utilizing one of their CCTV cameras. After the video snippets were gathered, the frames were extracted, resulting in 3200 frames.

3.3. Data Pre-Processing

3.3.1. Annotation

The MMDA labels the relevant objects in their surveillance systems as follows: all vehicles powered by motorized engines are identified as "vehicles", regardless of vehicle type; vehicles that are not powered by motorized engines will be classified according to their vehicle type, e.g. bicycle; Pedestrians are people walking on and alongside the streets designated for vehicles. Table 1 shows how many objects there are in each class.

Table 1: Number of objects per class

Pedestrian	Vehicles	Bicycle	Total
22612	72343	5180	100135

The region of interest of the pedestrian crossing lane and the street were also manually annotated. Additionally, the pedestrian crossing light is also annotated. These three objects are essential to the detection of illegal crossing and pedestrian lane obstruction as these are the conditions for the violator classifier algorithm. The annotations were manually configured to be a Python dict with the keys: labels and boxes, where the boxes have a format of {x1,y1,x2,y2}.

3.3.2. Data Cleaning

After the dataset was extracted from the annotation platform, the dataset was checked, where missing labels and some errors were identified. The missing labels were removed from the dataset while the other errors were fixed using algorithms.

These algorithms were used to open each JSON file and check each value. If a value has a '\n' or newline escape sequence, it is stripped from the value. Additionally, the coordinates of boxes that are higher than the image size are reduced to the image size. The boxes that were considered too small are boxes that have an area that is less than 100 pixels. These values are removed from the dataset.

3.3.3. Data Splitting

The researcher had done an 80:20 train-test split. Thus, the train set was allocated 2560 frames while the test set was allocated 640 frames. After the dataset was split, the class distribution is seen in Table 2.

Table 2: Distribution of categories of the dataset after data splitting

Set	Pedestrian	Vehicle	Bicycle	Total
Training	17063	52847	4150	74524
Testing	5549	19496	1030	25611

From 100,135 objects, the data was split to 74,524 total objects for the training dataset and 25,611 for the testing dataset. 17, 063 pedestrian objects were allocated to the training dataset, leaving 5, 549 for the testing dataset. The vehicle objects were divided into 4,150 and 1,030 for the training and testing set respectively. The bicycle was also divided by 4,150 and 1,030 in the same order.

3.3.4. Feature Transformation Module

Inspired by [15], a transformation module was introduced to improve the learning rate of the model through data normalization and data scaling. The module especially boosts the performance of the integrated SENet by preparing the raw data in such a way that the data is balanced and unbiased.

The dataset undergoes contrast limited adaptive histogram equalizer (CLAHE) to address the low illumination found in nighttime images. After the contrast is increased, the data is normalized to rescale the image values to a consistent range.

3.4. Configurations

The base model used for this study is Faster R-CNN [12, 14, 15, 16]. This model was made with Python 3.11, using the PyTorch ML Library. The base model was configured to improve its detection performance with the following networks:

3.4.1. ResNet34

To improve object detection, the VGG16 backbone of the Faster RCNN architecture is replaced with a pre-trained ResNet34 [12]. This ensures the complete transfer of information as the network consists of several convolutional layers and skip connections that assist in reducing vanishing gradient problems.

3.4.2. Squeeze and Excitation Network

The Feature Attention Module addresses the difficulties in classifying smaller objects at night by suppressing the background image noise and highlighting the object [16]. The Squeeze and Excitation network is used as the feature attention module to increase the performance of the feature extraction of the Faster RCNN model [12]. The addition of SENet will allow the model to alleviate missed detections in occluded objects [18]. By incorporating it into the backbone of the model at each convolutional block before the skip connection of ResNet34, the output of each block structure of the network is enhanced.

3.4.3. Feature Pyramid Network

The researcher also incorporated the FPN or Feature Pyramid Network after the backbone of the model to improve the detection of smaller targets. This network takes feature maps extracted from the ResNet-34 with SENet backbone and starting with the highest-level feature map, it is upsampled and then added to the corresponding feature map that was extracted from the backbone.

3.4.4. Violator Classifier Algorithm

Additionally, in the proposed system, the researcher created an algorithm, denoted in this study as the "Violator Classifier Algorithm", that will determine whether a pedestrian is jaywalking, or a vehicle is obstructing the pedestrian lane. The violator classifier algorithm takes the detections generated by the model and utilizes it to classify the violators. It also extracts the color information of the pedestrian crossing light from the input image.

Table 3: Violator Classifier Conditions for Pedestrians

Object's Location	Light is Green	Light is Red
The object is on the pedestrian lane.	Non-violator	Violator
The object is on the street but not on the pedestrian lane.	Violator	Violator
The object is both not on the street and the pedestrian lane.	Non-violator	Non-violator

Table 4: Violator Classifier Conditions for Vehicles and Bicycles

Object's Location	Light is Green	Light is Red
The object is on the pedestrian lane.	Violator	Non-violator
The object is not on the pedestrian lane.	Non-violator	Non-violator

Following the conditions in Table 3 and Table 4, the violator classifier algorithm first takes the objects detected by the model as input. Using the color information from the pedestrian crossing light which was done by taking the average color of the area of the pedestrian light, and location of each object, the objects are classified as either violators or non-violators.

3.5. Model Training and Testing

3.5.1. K-Fold Cross Validation

This technique was utilized by the researcher to train and validate the model. This technique allowed the researcher to maximize the data they had by training the model through different subsets of the dataset [7]. In utilizing this technique, the number of folds that was chosen was 5.

3.5.2. Training

During training, the model underwent supervised learning. For each fold, the training subsets, to be denoted as k – 1, are shuffled to diversify the dataset and to prevent overfitting to a certain sequence of data while the validation subset, to be denoted as k, remains unshuffled. The k – 1 subset is first used to train the model.

3.5.3. Evaluation

Done after K-Fold Cross Validation, the testing dataset is fed to the model and the performance of the model is measured using the metrics: precision (P), recall (R), average precision (AP), and mean average precision (mAP). Furthermore, to handle the class imbalance, the researcher decided to adjust the confidence threshold for each object [22]. The expression used to adjust the threshold is (n1 / n2) / (1 + n1 / n2), where n1 signifies the total count of objects per class and n2 signifies the total count of objects of the remaining classes. Since the bicycle class has a small amount, the threshold would be too low if the expression was followed. Thus, the confidence threshold for the bicycle class was 0.2 [22], while for the pedestrian class and the vehicle class, the thresholds were 0.23 and 0.72 respectively.

$$\mathrm{P}_{precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \cdot 100\ \% \tag{1}$$

$$R_{recall} = \frac{TP}{TP + FN} \cdot 100\ \% \tag{2}$$

$$AP_{average\ precision} = \int_0^1 P(R)\ dR \tag{3}$$

$$mAP_{mean\ average\ precision} = \frac{\sum_{i=1}^{N} AP_i}{\boldsymbol{N}} \tag{4}$$

where TP = True Positives, FP = False Positives, N = Total Number of Classes

3.5.4. Hyperparameter Tuning

After evaluating the model, the random search was done to tune the model's hyperparameters. A set of hyperparameters from each hyperparameter range is first randomly chosen as the hyperparameters of the model. The model undergoes K-Fold Cross Validation and model evaluation using the sampled combination of hyperparameters. After repeating this process 10 times, the model was trained with a batch size of 20, learning rate of 0.0025, weight decay of 0.005, and a momentum of 0.9.

4. Results and Discussion

Based on the evaluation metrics, the researcher was able to look how the model performed to new and unseen data, which was the testing set, in Table 5.

Table 5: Model Performance Metrics

Class	**Precision**	**Recall**	**AP**
Pedestrian	0.3075	0.3138	0.206
Vehicle	0.9065	0.7339	0.7216
Bicycle	0.3151	0.699	0.5054

Overall, the model had a mean average precision of 47.77%. With a precision of 30.75% and 31.51% on pedestrians and bicycles respectively, the model struggled with these classes. It did, however, handle the bicycle better, as seen in its recall rate and AP rate. The model did well in detecting vehicles, maintaining a high score throughout all the metrics.

Table 6: Tabulated Pedestrian Confusion Matrix

Class	**Objects per class**	**TP**	**FP**	**FN**
Non-Violator	1814	603	1451	1211
Violator	3735	1291	9298	2444

Table 7: Tabulated Vehicle Confusion Matrix

Class	**Objects per class**	**TP**	**FP**	**FN**
Non-Violator	18606	13469	1444	5137
Violator	890	816	488	74

Table 8: Tabulated Bicycle Confusion Matrix

Class	**Objects per class**	**TP**	**FP**	**FN**
Non-Violator	1030	720	1469	310
Violator	0	0	43	0

Table 6 showed that the model had identified a few true positives when detecting pedestrians, 603 out of 1814 on non-violating pedestrians and 816 out of 890 on violating pedestrians. With false positives and false negatives of 1451 and 1211, and 9298 and 2444 on non-violating pedestrians and violating pedestrians respectively, the model had struggled on this class. On Table 8, however, it could be seen that the model was able to identify more than half of the true positives, 720 out of 1030 on non-violating bicycles. The bicycle did have some false negatives- 310 for non-violators and 43 for violators, in which there were no classified violators in the test dataset. This could be attributed to the model's misclassifications of pedestrians. The model performed well in detecting vehicles, especially non-violating vehicles, as seen in Table 7. It did have a high false positive count in detecting violating vehicles. This could also be attributed to how the model confuses pedestrians with motorcycles.

To measure the improvement of the model, the researcher had chosen to compare its performance to the base Faster RCNN architecture, to be denoted as Base, and the Faster RCNN with ResNet50 backbone and FPN, to be denoted as ResNet50-FPN. The following tables below show the performance of the model measured using the performance metrics.

Table 9: Comparison of results based on Precision

Model	**Pedestrian**	**Vehicle**	**Bicycle**
Base	0.0514	0.7323	0.1547
ResNet50-FPN	0.1644	0.8376	0.2414
Ours	0.3075	0.9065	0.3151

Table 10: Comparison of results based on Recall

Model	**Pedestrian**	**Vehicle**	**Bicycle**
Base	0.4156	0.6103	0.6544
ResNet50-FPN	0.5145	0.7474	0.7903
Ours	0.3138	0.7339	0.699

Table 11: Comparison of results based on Average Precision

Model	**Pedestrian**	**Vehicle**	**Bicycle**
Base	0.077	0.536	0.359

ResNet50-FPN	0.1427	0.6957	0.5555
Ours	0.206	0.7216	0.5054

Table 12: Comparison of results based on Mean Average Precision

Model	Mean Average Precision
Base	0.324
ResNet50-FPN	0.4646
Ours	0.4777

The proposed model has a lower recall than the ResNet50-FPN, and Base in detecting pedestrians. Despite this, significant improvement could be seen in the other metrics, especially between the base Faster RCNN and the proposed model in the Precision metric. An overall improvement of 15.37% could be seen from the base Faster RCNN and 1.31% from the ResNet50-FPN.

5. Conclusion

With the enhanced images output by CLAHE, the proposed model could detect objects that are more affected by low illumination and background noise. The addition of the Squeeze and Excitation Network and Feature Pyramid Network, on the other hand, improved the feature extraction of the model. This boosted the model's capability of detecting smaller objects such as pedestrians.

However, the model did struggle to distinguish the difference between pedestrians, bicycles, and vehicles, often leading to false positives. Despite the low metric scores, the model showed improvement by 15.37% when compared to the unmodified Faster RCNN algorithm in conducting nighttime detection in the mean average precision metric. Additionally, when compared to the Faster RCNN with a Resnet50 backbone and FPN, the proposed model showed a better performance by 1.31%.

There are limitations to this study, however, which include using the proposed model in a different setup with different perspectives and orientations as the model was trained from one setup only. This would mean that inputs that have a different setup result in lower performance. Additionally, there are false negatives and false positives in detecting pedestrians and bicycles. In future studies, these limitations could be addressed by incorporating different setups and a bigger dataset for training.

Acknowledgements

The author would like to take the opportunity to thank Mr. John Paul Q. Tomas for being their adviser, guiding and assisting the author, and allowing the author to have this opportunity to publish this paper.

References

[1] Adrian Tamayo. 2009. Occurrence of Traffic Accidents in the Philippines: An Application of Poisson Regression Analysis. DOI:https://doi.org/10.2139/ssrn. 1438478.

[2] Reddy Alexandro Harianto, Yuliana Melita Pranoto, and Tjwanda Putera Gunawan. 2021. Data Augmentation and Faster RCNN Improve Vehicle Detection and Recognition. In 2021 3rd East Indonesia Conference on Computer and Information Technology (EIConCIT), IEEE, Surabaya, Indonesia, 128–133. DOI:https://doi.org/10.1109/EIConCIT50028.2021.9431863.

[3] Neha Sharma, S. Indu, and Chhavi Dhiman. 2022. A Deep Unified Pedestrian Detection Framework. In 2022 IEEE Delhi Section Conference (DELCON), IEEE, New Delhi, India, 1–6. DOI:https://doi.org/10.1109/DELCON54057.2022.9753544.

[4] XinXin Huang, ZhenYu Yin, and Chao Fan. 2022. Towards Better Pedestrian Detection Using Multi-Scale CSPN and Dual Attention. In 2022 11th International Conference of Information and Communication Technology (ICTech)), IEEE, Wuhan, China, 451–456. DOI:https://doi.org/10.1109/ICTech55460.2022.00096.

[5] Jiaqi Zhang, Xunlei Chen, Yingling Li, Tianxiang Chen, and Liqiang Mou. 2021. Pedestrian detection algorithm based on improved Yolo v3. In 2021 IEEE International Conference on Power, Intelligent Computing and Systems (ICPICS), IEEE, Shenyang, China, 180–183. DOI:https://doi.org/10.1109/ICPICS52425.2021.9524267.

[6] Yangzhi Wang, Ruibin Zou, Yilu Chen, and Zhenxing Gao. 2023. Research on Pedestrian Detection Based on Jetson Xavier NX Platform and YOLOv4. In 2023 4th International Symposium on Computer Engineering and Intelligent Communications (ISCEIC), IEEE, Nanjing, China, 373–377. DOI:https://doi.org/10.1109/ISCEIC59030.2023.10271216.

[7] Yuqiao Gai, Weiyang He, and Zilong Zhou. 2021. Pedestrian Target Tracking Based On DeepSORT With YOLOv5. In 2021 2nd International Conference on Computer Engineering and Intelligent Control (ICCEIC), IEEE, Chongqing, China, 1–5. DOI:https://doi.org/10.1109/ICCEIC54227.2021.00008.

[8] Zhengyan Liu, Chaoyue Dai, and Xu Li. 2023. Pedestrian Detection Method in Infrared Image Based on Improved YOLOv7. In 2023 IEEE 3rd International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), IEEE, Chongqing, China, 946–954. DOI:https://doi.org/10.1109/ICIBA56860.2023.10165354.

[9] Yunchuan Wu, Cheng Chen, and Bo Wang. 2022. Pedestrian Detection Based on Improved SSD Object Detection Algorithm. In 2022 International Conference on Networking and Network Applications (NaNA), IEEE, Urumqi, China, 550–555. DOI:https://doi.org/10.1109/NaNA56854.2022.00101.

[10] Enji Sun, Xu Ma, and Mingze Li. 2022. Improved SSD based pedestrian detection algorithm for forklift active warning system. In 2022 IEEE 5th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), IEEE, Chongqing, China, 1523–1528. DOI:https://doi.org/10.1109/IMCEC55388.2022.10019947.

[11] T T Feng and H Y Ge. 2020. Pedestrian detection based on attention mechanism and feature enhancement with SSD. In 2020 5th International Conference on Communication, Image and Signal Processing (CCISP), IEEE, Chengdu, China, 145–148. DOI:https://doi.org/10.1109/CCISP51026.2020.9273507.

[12] Chunling Yang and Dong Qiu. 2022. Pedestrian Detection Based on Improved Faster-RCNN Algorithm. In 2022 IEEE Inter-national Conference on Real-time Computing and Robotics (RCAR), IEEE, Guiyang, China, 378–383. DOI:https://doi.org/10.1109/RCAR54675.2022.9872220.

[13] Sweta Panigrahi and U.S.N. Raju. 2021. An improved Faster RCNN for Pedestrian Detection. In 2021 International Conference on Control, Automation, Power and Signal Processing (CAPS), IEEE, Jabalpur, India, 1–6. DOI:https://doi.org/10.1109/CAPS52117.2021.9730492.

[14] Xiaoqiang Shao, Jinyang Wei, Defeng Guo, Runyang Zheng, Xinchao Nie, Guowei Wang, and Yu Zhao. 2021. Pedestrian Detection Algorithm based on Improved Faster RCNN. In 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), IEEE, Chongqing, China, 1368–1372. DOI:https://doi.org/10.1109/IAEAC50856.2021.9390882.

[15] S. Devi, R. Dayana, and P. Malarvezhi. 2023. Improved Faster RCNN-based Nighttime Pedestrian Detection Using RGB Images. In 2023 International Conference on Intelligent Systems for Communication, IoT and Security (ICISCoIS), IEEE, Coimbatore, India, 7–12. DOI:https://doi.org/10.1109/ICISCoIS56541.2023.10100389.

[16] Gang Li, Shanshan Zhang and Jian Yang, "Nighttime Pedestrian Detection Based on Feature Attention and Transformation," 2020 25th International Conference on Pattern Recognition (ICPR), Milan, Italy, 2021, pp. 9180-9187, DOI: 10.1109/ICPR48806.2021.9412889.

[17] John Paul Q. Tomas, Shaina Nicole V. Jocsing, James Kirk L. Guanzon, and Chielo Jane A. Matias. 2019. Effectiveness of Haar-like Features and ViBe Algorithm for Detecting Jaywalkers. In Proceedings of the 2019 2nd International Conference on Computational Intelligence and Intelligent Systems, November 23, 2019, Bangkok Thailand. ACM, Bangkok Thailand, 90–98. . DOI: https://doi.org/10.1145/3372422.3372436.

[18] Qiangbo Zhang, Yunxiang Liu, Yu Zhang, Ming Zong, and Jianlin Zhu. Improved YOLOv3 Integrating SENet and Optimized GIoU Loss for Occluded Pe-destrian Detection. Sensors. 2023; 23(22):9089. DOI: https://doi.org/10.3390/s23229089.

[19] Li, Y., Luo, Y., Zheng, Y., Liu, G., Gong, J. Research on Target Image. 2024. Classification in Low-Light Night Vision. Entropy 2024, 26, 882. DOI: https://doi.org/10.3390/e26100882.

[20] Guo Xiaoying, Liu Qiaoling, Qin Zhikang, and Xu Yan. 2021. Target Detection of Forward Vehicle Based on Improved SSD. In 2021 IEEE 6th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA), IEEE, Chengdu, China, 466–468. DOI:https://doi.org/10.1109/ICCCBDA51879.2021.9442550.

[21] Sangeeth Mathew John, Fathima Abdul Kareem, Sachin Gee Paul, Abdul Gafur M, Saeed Al Mansoori, and Alavikunhu Panthakkan. 2023. Enhanced YOLOv7 Model for Accurate Vehicle Detection from UAV Imagery. In 2023 International Con-ference on Innovations in Engineering and Technology (ICIET), IEEE, Muvattupuzha, India, 1–4. DOI:https://doi.org/10.1109/ICIET57285.2023.10220850.

[22] F. Xang, X. Zhang, S. Zhang, C. Li, and H. Hu, “Design of real-time vehicle detection based on YOLOv4,” 2021 International Conference on Control, Automation and Information Sciences (ICCAIS), Xi’an, China, 2021, pp. 824-829, DOI: 10.1109/ICCAIS52680.2021.9624546.