Detection of Helmets in Single and Multiple Motorcycle Riders using YOLOv8

John Paul Q. Tomas
School of Information Technology, Mapúa University, jpqtomas@mapua.edu.ph

Jan Edgar E. Tupas
School of Information Technology, Mapúa University, jeetupas@mymail.mapua.edu.ph

Miguel T. Soniel
School of Information Technology, Mapúa University, mtsoniel@mymail.mapua.edu.ph

Christian Henry Miguel E. Caruz
School of Information Technology, Mapúa University, chmecaruz@mymail.mapua.edu.ph

Darryll B. Babar
School of Information Technology, Mapúa University, dbbabar@mymail.mapua.edu.ph
This study aims to present and develop an object detection model using the YOLOv8 algorithm to accurately detect motorcycle riders and their helmets in various conditions. Our study uses a dataset sourced from several videos, utilizing images of the riders with their different helmet types (full-faced, half-faced, invalid, and no helmet) and the number of passengers in the motorcycle (single, double, and triple). Data preprocessing techniques are applied to improve the quality of the dataset and to balance the issues for the address classes. The YOLOv8 Medium model was used for the detection task and was evaluated using metrics such as the mean average precision, precision, and recall. The study obtained average but promising results with scores of mAP@50 of 66.2%, precision of 68.2%, and recall of 62%. Recommendations include improving dataset balance, exploring advanced preprocessing methods, and further hyperparameter tuning to enhance model performance. The study contributes to the field of object detection in real-world scenarios, specifically targeting motorcycle safety and traffic management applications.

CCS CONCEPTS • Computing methodologies~Machine learning • Computing methodologies~Artificial intelligence • Applied computing~Physical sciences and engineering~Earth and atmospheric sciences~Environmental sciences

Additional Keywords and Phrases: motorcycle detection, object detection, YOLOv8, helmet detection

1 INTRODUCTION

Motorcycles are a popular mode of transportation that individuals prefer due to the convenience they provide. According to statistics provided by Statista, the number of registered motorcycles and tricycles in the Philippines increased from 2020 to 2022, with approximately 7.81 million registered motorcycles and tricycles recorded in 2022 [9]. Motorcycles are used as both private and public forms of transportation, as well as for delivery services, highlighting the importance and prevalence of motorcycles in the country [5]. However, the dangers of motorcycles as a transportation method must be considered.

Motorcycles pose safety risks that may result in fatal accidents, harming the welfare of riders. According to the Metropolitan Manila Development Authority, a total of 26,599 motorcycle-related road crashes were recorded in 2022, with 278 cases being fatal [4]. Additionally, a total of 17,778 people were recorded to be involved in motorcycle-related road crashes. It is vital to ensure the safety of motorcycle riders to lessen and avoid motorcycle-related accidents effectively. According to Seva. [11], one of the significant predictors of serious injuries in motorcycle-related accidents is the non-usage of helmets, and helmets effectively reduce the injury of motorcycle riders in accidents. Republic Act No. 10054, also known as the Motorcycle Helmet Act of 2009, requires all motorcycle riders to wear protective helmets, ensuring their safety in crashes or accidents [10]. Any person who is caught violating the act is subject to punishments ranging from first to fourth offense, and in the form of fines, as well as the confiscation of license. Thus, validating that all motorcycle riders wear protective helmets is essential to mitigate the risks of fatal motorcycle-related accidents.

In this study, the researchers developed an object detection model for detecting motorcycle riders and helmets. Specific helmet types were detected, namely full-faced and half-faced helmets, invalid helmets or helmets not for motorcycle purposes, and no helmets. The number of motorcycle riders was also detected, including single, double, and triple riders. The YOLOv8 detection algorithm, specifically the YOLOv8 Medium model, was used in the study due to its efficacy in object detection tasks.

The primary objective of the study was to develop a YOLOv8 model to detect motorcycle helmets worn by riders accurately and effectively. The specific objectives of the study are the following: (1) To develop a YOLOv8 model that can accurately and effectively detect motorcycle helmets worn by riders and the number of riders using the created dataset; (2) To enhance the YOLOv8 model through hyperparameter tuning, specifically modifying the batch size, epoch, and learning rate hyperparameters; (3) To evaluate the performance of the YOLOv8 model in detecting and classifying each specified class.

2 REVIEW OF RELATED LITERATURE

The researchers performed a literature review to gain insights from previously conducted related studies. An overview and discussion of related literature relating to the detection of motorcycle helmets using deep learning are presented in this section.

2.1 Detection of Motorcycle Helmet

Various deep learning studies have tackled the detection of motorcycle helmets using various object detection algorithms. Sanchana et al. proposed in their study [3] the automatic detection of motorcycle helmets using a combined YOLO and CNN model. The authors collected and annotated motorcycle images of riders wearing or not wearing helmets. To improve the quality of the photos, the authors performed image pre-processing through image resizing, flipping, cropping, and data augmentation. The authors leveraged CNN and YOLO algorithms for the detection task. A CNN was first trained with the annotated images and was used to extract features. Afterward, the YOLO algorithm was used to take the images as input, split them into tiny cells, and perform helmet detection. The authors achieved an accuracy of 94.29%.

Studies also use other deep learning algorithms besides YOLO for motorcycle helmet detection. In the study of Bouhayane et al. [7], the authors proposed the use of the Swin Transformer, Feature Pyramid Network (FPN), and Cascade Region-based Convolutional Neural Network (RCNN). The Swin Transformer was used for feature extraction. Meanwhile, for helmet use detection, the RCNN with FPN was used. A dataset of 91,000 images collected from traffic video in Myanmar was used in the study. The model was fine-tuned for 12 epochs with a batch size of 2 and with the AdamW optimizer. The transformer-based model achieved an mAP of 30.4%, achieving the best performance compared to other models.

2.2 YOLOv8 Algorithm

There have been numerous variants of the YOLO algorithm. It is a highly effective algorithm for object detection tasks, making it a standard tracking method that swiftly recognizes different objects. In YOLOv8, two neural networks, the Feature Pyramid Network (FPN) and the Path Aggregation Network (PAN), are implemented, and a new labeling tool is used to make annotation easier [2]. YOLOv8 separates objectness, classification, and regression tasks using an anchor-free model with a decoupled head [1]. Allowing each branch to concentrate on its specific task improves the model's overall accuracy. Various YOLO variants were evaluated for object detection in satellite images in the study of Adegun et al. [8]. Upon comparing the YOLOv8 model with Detectron2 and YOLOv5, YOLOv6, and YOLOv7, the YOLOv8 model achieved the best performance with a precision of 68% and recall of 60%. In the study of Chitraningrum et al. [6], the authors evaluated YOLOv5 and YOLOv8 for detecting corn leaf disease. Both models were able to identify infected corn leaves. The YOLOv8 model was found to be better at detecting the infected spots as opposed to the YOLOv5 mode.

3 METHODOLOGY

The methods and materials utilized in the study are discussed in this section. Using the online platform YouTube, the researchers sourced traffic videos that contained motorcycle riders with helmets. Images were extracted from the video, and image preprocessing methods were applied to enhance the quality of the dataset in preparation for modeling. The data was then used as input into an object detection model for training, validation, and testing. The model was then adjusted through hyperparameter tuning in an attempt to enhance model performance. The methodology of the study comprises the following stages: data collection, data preprocessing, model development, and model performance evaluation. Figure 1 illustrates the conceptual framework of the study.

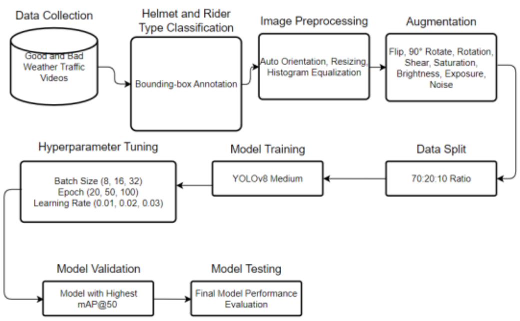

Figure 1: Conceptual Framework of the Study

3.1 Data Collection

A dataset of motorcycle riders and helmets was curated by the researchers and used in the study. The researchers searched for traffic videos using the online platform YouTube. Four videos were acquired, two of which had good weather and lighting conditions, while the remaining two had rainy weather and partially low lighting conditions. In this way, variety was introduced in the dataset due to the different weather and lighting conditions. The collected videos were inspected, and sections of the videos that included motorcycle riders were extracted. Afterward, all video snippets were merged and compiled into one whole video. The result was a 10-minute video showing motorcycle riders in good and bad weather conditions.

3.2 Dataset

The researchers used a 10-minute video that contained instances of motorcycle riders to extract images and create the dataset. Using the online platform Roboflow, the footage was sampled by three frames per second. After sampling, a total of 1601 images were acquired. Seven classes were used for the object detection task. The classes were full-faced, half-faced, invalid, and no-helmet, which centered on the motorcycle helmet type of the riders, and single, double, and triple, which focused on the number of riders in a motorcycle. The ground truth was acquired by manually counting the total number of instances for each class, as shown in Table 1. It can be observed that the dataset was imbalanced. For helmet type, invalid and no-helmet types were the minority class. For the number of riders, triple was the minority class. Data augmentation was performed in an attempt to mitigate the impact of the dataset imbalance, resulting in a total of 3843 images.

Table 1: **Total Instances of Each Class**

Class	Total Instance
Full-faced	2235
Half-faced	2945
Invalid	267
No-helmet	167
Single	3305
Double	1274
Triple	18
Total	10211

3.3 Data Preprocessing

Enhancing the quality of images can impact the performance of the model for the object detection task. This is achieved through various data preprocessing techniques. Using Roboflow, the researchers implemented multiple data preprocessing techniques to modify the quality of the dataset. Data annotation was first performed by the researchers. The images were annotated with bounding boxes to identify and label the classes observed in each image. The classes used were full-faced, half-faced, invalid, and no-helmet for motorcycle helmets and single, double, and triple for motorcycle riders. Afterward, auto-orientation and image resizing to 640x640 were done. This ensures compatibility with the model and better optimization. Histogram equalization was applied to the images as an auto-adjusting contrast step to improve the contrast of the images, which can enhance the efficacy of the model. In this way, the visibility of objects in the images was enhanced, especially in the images with bad weather and low light conditions. The researchers split the data into training, validation, and test sets using a ratio of 70:20:10, which is a standard ratio used for dataset splitting. The dataset consisted of 1601 images. The researchers artificially expanded the dataset using data augmentation. This helps mitigate the impact of the dataset imbalance and overfitting while enhancing the robustness and generalization of the object detection model. Various data augmentation methods with differing parameters were applied, as shown in Table 2. Overall, the dataset included 3843 images. The training, validation, and test sets included 3363, 321, and 159 images, respectively.

Table 2: **Applied Data Augmentation Methods**

Augmentation Technique	Type
Flip	horizontal
90° Rotation	clockwise, counter-clockwise
Rotation	-45° to +45°
Shear	+-10° horizontal, +-10° vertical
Saturation	-30% to +30%
Brightness	-20% to +20%
Exposure	-15% to +15%
Noise	up to 0.1% pixels

3.4 Model Training and Validation

The researchers developed an object detection model for the detection of motorcycle helmets, classification of helmet type, and detection of the number of riders in a motorcycle. The researchers utilized the YOLOv8 algorithm for the object detection task. Specifically, the YOLOv8 Medium variant was used in the study. The dataset consisted of a significant number of images, but better model performance can be achieved with more data. Because of this, the researchers utilized a YOLOv8 model pre-trained on the COCO dataset to prevent training from scratch while allowing for better model performance. The online platform Google Colab was used to develop the YOLOv8 model, along with a T4 GPU. The YOLOv8 model was custom-trained using the created dataset. Hyperparameter tuning was carried out to evaluate the performance of the model on specific hyperparameter combinations in an attempt to enhance the overall performance of the model. The hyperparameters modified were batch size, epoch, and learning rate. Table 3 shows the hyperparameter combinations used in the study. TensorBoard was used to visualize and note the performance of the model using the hyperparameter combinations all throughout the training phase. After training, the models were further evaluated using the validation set to identify which model produced the best results.

Table 3: Hyperparameter Combinations

Class	Batch Size	Epoch	Learning Rate
1	8	20	0.01
2	16	50	0.02
3	32	100	0.03

3.5 Testing

Upon completion of the validation phase, the model with the best performance was identified and chosen for the testing phase. Data from the test set was fed into the model to evaluate the performance of the model when dealing with unseen data, simulating model deployment on real-world data. In this way, the capacity of the model to generalize with new data and to operate with real-world data was evaluated and assessed. The performance metrics used to evaluate the performance of the model were mean average precision at an IoU threshold of 0.5 (mAP50), Precision (P), and Recall (R). The confusion matrix was also used to assess the performance of the model in correctly detecting and classifying the specific object classes as specified in the study.

4 RESULTS AND DISCUSSION

The results acquired from the developed YOLOv8 model for detecting motorcycle riders with helmets are presented in this section. The performance of the model for the object detection task, the results of hyperparameter tuning, and the performance of the model in classifying the detected objects are discussed.

4.1 Model Training, Hyperparameter Tuning, and Validation

The researchers developed a pre-trained YOLOv8 Medium model to detect motorcycle helmets and riders. Training and validation were conducted using the train and validation sets of the created dataset. Hyperparameter tuning was implemented to identify which combination of hyperparameters resulted in the best performance for the object detection task. The researchers modified the batch size, epoch, and learning rate parameters and compared the results. The optimizer used for all models was Stochastic Gradient Descent (SGD) and was not changed all throughout the study. Table 4 shows the validation results of the developed model with the specific combination of hyperparameters used.

Table 4: **Validation Results**

Combination 1	Batch Size (8)	Epoch (20)	Learning Rate (0.01)
Classes	mAP@50	Precision	Recall
All	0.642	0.601	0.674
Full-faced	0.537	0.538	0.556
Half-faced	0.473	0.489	0.547
Invalid	0.43	0.453	0.32
No-helmet	0.346	0.384	0.548
Single	0.888	0.74	0.89
Double	0.823	0.675	0.855
Triple	0.995	0.849	1
Combination 2	Batch Size (16)	Epoch (50)	Learning Rate (0.02)
Classes	mAP@50	Precision	Recall
All	0.669	0.669	0.513
Full-faced	0.573	0.617	0.513
Half-faced	0.536	0.627	0.486
Invalid	0.468	0.592	0.281
No-helmet	0.377	0.402	0.645
Single	0.901	0.812	0.883
Double	0.832	0.759	0.838
Triple	0.995	0.871	1
Combination 3	Batch Size (32)	Epoch (100)	Learning Rate (0.03)
Classes	mAP@50	Precision	Recall
All	0.701	0.69	0.687
Full-faced	0.574	0.673	0.554
Half-faced	0.555	0.615	0.516
Invalid	0.516	0.555	0.373
No-helmet	0.523	0.504	0.645
Single	0.89	0.831	0.89
Double	0.831	0.753	0.831
Triple	0.897	0.897	1

In the study, an epoch of 20, 50, and 100 were used and evaluated, but the loss illustrations show that the graph still continues to descend. This implies that improvements on the model can still effectively continue after the 100th epoch. The validation results describe the detection and classification performance of the model. In observing the values of mAP@50, the performance of the model is improved upon increasing the values for batch size, epoch, and learning rate. The combination 3 model achieved the highest metrics scores, with 70.1% for mAP@50, 69%% for precision, and 68.7% for recall. The model with hyperparameter combination 3 obtained better performance in terms of mAP@50 by 5.9% from the combination 1 model and by 3.2% from the combination 2 model. The combination 3 model gained improved precision scores by 8.9% and 2.1% from the combination 1 model and the combination 2 model, respectively. Recall scores were also the highest from the combination 3 model, increasing by 1.3 % from the combination 1 model and 17.4% from the combination 2 model. Meanwhile, the performance of the models in classifying the helmet type and the number of riders on the motorcycle varies. In terms of helmet types, the models had average performance in detecting full-faced helmets, half-faced helmets, and no helmets, but struggled in classifying invalid helmet instances. For riders, the models show good efficacy for detecting single, double, and triple riders where the obtained mAP@50 scores were all above 80%. Overall, the validation results show that the model with the hyperparameter combination of a batch size of 32, epoch of 100, and learning rate of 0.03 produced the best results out of all three specified combinations for the object detection task. The validation scores acquired signify that there is still room for improvement, as the mAP@50 scores obtained were contained between 60% and 70%. Increasing the value for epoch during training can further increase the performance of the model as it will have more time to learn from the input data. Along with the epoch, modifying and increasing the value of the learning rate could also potentially improve model performance to speed up convergence while generating more significant updates to the weights of the model.

4.2 Evaluating Model Classification Performance

Table 5: Combination 1 Confusion Matrix

	Class	True							
		Double	Full-faced	Half-faced	Invalid	No-helmet	Single	Triple	Background
Predicted	Double	184	1	0	0	21	21	0	63
	Full-faced	0	175	55	1	1	0	0	87
	Half-faced	0	82	260	18	1	1	0	137
	Invalid	0	2	1	14	1	0	0	11
	No-helmet	0	0	0	11	16	0	0	11
	Single	20	2	1	0	0	513	0	131
	Triple	0	0	0	0	0	0	5	0
	Background	24	110	206	23	12	63	0	0

Table 6: Combination 2 Confusion Matrix

	Class	True							
		Double	Full-faced	Half-faced	Invalid	No-helmet	Single	Triple	Background
Predicted	Double	194	0	1	0	0	11	0	50
	Full-faced	0	192	54	3	1	0	0	94
	Half-faced	0	77	263	10	3	0	0	116
	Invalid	0	2	4	18	1	0	0	9
	No-helmet	0	0	3	12	20	0	0	16
	Single	13	2	0	0	0	528	0	117
	Triple	0	0	0	0	0	0	5	0
	Background	21	99	198	24	6	59	0	0

Table 7: Combination 3 Confusion Matrix

	Class	True							
		Double	Full-faced	Half-faced	Invalid	No-helmet	Single	Triple	Background
Predicted	Double	192	1	1	0	0	6	0	65
	Full-faced	0	217	57	0	0	0	0	70
	Half-faced	0	64	292	13	3	0	0	131
	Invalid	0	2	6	28	0	0	0	19
	No-helmet	0	0	1	12	21	0	0	10
	Single	15	2	0	0	0	542	0	106
	Triple	0	0	0	0	0	0	5	1
	Background	21	86	166	14	7	50	0	0

The tables 5, 6, and 7 presented above show the confusion matrices of the models utilizing the different combinations of hyperparameters. It can be observed that there is a significant portion of instances of the specific helmet type that were correctly classified by the detection model. Although many instances of full-faced and half-faced helmets were correctly predicted, there were still instances that needed to be identified. Some instances of full-faced helmets were misclassified as half-faced helmets and vice versa. This can be attributed to the similar look of both helmets, where only the protection of the chin provides the difference between the helmets. Some images of helmets are quite small and unclear, resulting in the misclassification of the model. Furthermore, there are images where the helmet is seen in the front view and the side view, which hinders the visibility of the chin area, potentially leading to misclassification. Instances of the invalid class were also misclassified. This can be attributed to the similar look of invalid helmets to full-faced and half-faced helmets when viewed from the images. Meanwhile, for the classes that specify the number of riders in a motorcycle, it can be observed that the model was able to classify the images accordingly, with few misclassifications as compared to those for the helmet type. The model was able to classify triple riders with little error. Additionally, single and double riders had significant instances that were correctly classified and with minimal error. However, there were still some instances where the single riders were classified as double. For the double class, some instances were classified as single, which may be attributed to limited visibility. In this case, some instances of double riders looked similar to single riders because the second rider was covered by the first rider, showing only small portions of the head or body. This may be attributed to instances where two separate single-rider motorcycles were too close to each other, leading to a misclassification. It is, however, important to note that a significant number of object instances were misclassified by the model as background. This means that there are instances where the model completely fails to detect the presence of the object in the image. This could be attributed to the limited visibility of the objects in the images. This can be observed in the images of traffic, where the images of motorcycle riders were quite small and far from the point-of-view of the camera that took the image. As such, some object instances were not detected even though they were truly present. Overall, the model shows promising but limited results in correctly detecting the objects per class. There is still room for improvement in enhancing the performance capacity of the model.

4.3 Model Testing and Inference

After acquiring the results from the validation stage, the researchers identified the combination 3 model, or the model with the hyperparameter combination of a batch size of 32, epoch of 100, and learning rate of 0.03, as the model that attained the best performance. The model was tested using the images from the test set to determine the overall performance of the model with data it has yet to see. This simulates the deployment of the model with real-world data. Table 8 shows the test results of the model. Figure 2 shows sample outputs from the model.

Table 8: Test Results

Class	Images	Instances	mAP@50	Precision	Recall
All	159	900	0.662	0.682	0.62
Full-faced	159	155	0.545	0.644	0.561
Half-faced	159	288	0.556	0.72	0.438
Invalid	159	24	0.559	0.709	0.417
No-helmet	159	11	0.759	0.727	0.818
Single	159	302	0.876	0.874	0.825
Double	159	118	0.843	0.8	0.781
Triple	159	2	0.5	0.5	0.5

Figure 2: Model Detection Output

With the test images, the model performed at an average efficacy. The model obtained a mAP@50 of 66.2%, a precision score of 68.2%, and a recall of 62%. The obtained metric scores indicate that the model promising results for the detection task with room for improvement. In evaluating the metrics per class, the model achieves high scores for detecting no-helmet types with a mAP@50 of 75.9%, precision of 72.7%, and recall of 81.8%. Meanwhile, the model also achieves high scores in detecting single riders, obtaining a mAP@50 of 87.6%, precision of 87.4%, and recall of 82.5%. This signifies the potential of the model for the object detection task. However, the model still needs to show better performance in observing the metric scores for detecting the other classes. The lower scores indicate that improvements can still be implemented to the model to enhance its performance further. This can be achieved by modifying the hyperparameters and evaluating the impact on the model. Furthermore, feeding more data of better quality and more instances of each class can enhance the performance of the model. Overall, the model attained notable performance, but there is still room for improvement.

5 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In the study, the researchers developed a YOLOv8 model for the detection of motorcycle riders and helmets. A dataset of motorcycle rider images was created by the researchers, extracted from videos of motorcycle riders in good and bad weather conditions. The researchers implemented preprocessing techniques to enhance the quality of the dataset. Through data augmentation, the researchers artificially increased the size of the dataset from 1601 images to 3843 images. In developing the model, the researchers performed hyperparameter tuning centered on batch size, epoch, and learning rate. Three combinations were used, and the researchers evaluated the performance of the model for each combination. The validation results showed that the model with a batch size of 32, an epoch of 100, and a learning rate of 0.03 produced the best performance. The researchers tested the model with the test set images and obtained a mAP@50 of 66.2%, a precision score of 68.2%, and a recall of 62%, signifying average but promising performance. Furthermore, the researchers evaluated the performance of the model for specifically detecting each object class. The researchers observed that the model performs well in detecting no-helmets but limitations were found in detecting full-faced, half-faced and invalid helmets. The researchers also observed that the model is effective in detecting single riders and double riders but has average efficacy in detecting triple riders. The struggles of the model can be attributed to instances in the images where visibility was limited due to aspects like angle, lighting, size, and merging. The developed YOLOv8 model for detecting motorcycle riders and helmets showed average efficacy but promising results, requiring improvements to enhance the performance of the model further.

5.2 Recommendation

The researchers acknowledge the limitations of the study. One limitation is the dataset. Although the dataset consisted of a variety of conditions due to the different angles, weather, and lighting of the images and different sizes of the object instances, the dataset was imbalanced, where some classes had more total instances compared to other classes. The researchers recommend improving the dataset by collecting data with equal and sufficient representation for all classes to mitigate the impact of an imbalanced dataset on model performance. The researchers also recommend utilizing more image preprocessing techniques to enhance the quality of the dataset. It is recommended to explore different deep learning-based image preprocessing methods, such as low-light enhancement. In the study, the researchers only explored three hyperparameter combinations using batch size, epoch, and learning rate. The researchers recommend expanding the hyperparameter tuning phase by further exploring different values and combinations. Doing so could determine which combination results in the best model performance. Additionally, hyperparameters such as anchors, momentum, and weight decay can further be used and evaluated. Lastly, the researchers recommend developing the object detection model with new and different deep learning algorithms for the detection of motorcycle riders and helmets and comparing the results to the developed YOLOv8 model in the study. The developed model can still be further improved to enhance model performance and to deploy the model in applications that implement the detection of motorcycle riders and helmets in real time.

ACKNOWLEDGMENTS

The researchers would like to recognize and express their appreciation to their advisor, Prof. John Paul Tomas for support in this study. For this study, his supervision was essential. Additionally, the researchers would like to thank everyone who helped for the completion of this research study.

REFERENCES

<bib id="bib1"><number>[1]</number>Juan Terven, Diana-Margarita Córdova-Esparza, and Julio-Alejandro Romero-González. 2023. A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS. Mach. Learn. Knowl. Extr. 2023, 5(4), 1680–1716. DOI: https://doi.org/10.3390/make5040083</bib>
<bib id="bib2"><number>[2]</number>Indri Purwita Sary, Edmund Ucok Armin, and Safrian Andromeda. 2023. Performance Comparison of YOLOv5 and YOLOv8 Architectures in Human Detection Using Aerial Images. Ultima Computing: Jurnal Sistem Komputer, 15, 8-13. DOI: http://dx.doi.org/10.31937/sk.v15i1.3204</bib>
<bib id="bib3"><number>[3]</number>Mary Anne Sanchana and Sherin Eliyas. 2023. Automated Motorcycle Helmet Detection Using the Combination of YOLO and CNN. In Proceedings of the 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), 75-77. DOI: https://doi.org/10.1109/ICACITE57410.2023.10183003</bib>
<bib id="bib4"><number>[4]</number>Metropolitan Manila Development Authority (MMDA). 2022. MMDA- TEC- ROAD SAFETY UNIT MMARAS Annual Report 2022. </bib>
<bib id="bib5"><number>[5]</number>Asian Development Bank (ADB). 2020. Growth of Motorcycle Use in Metro Manila: Impact on Road Safety. DOI: https://dx.doi.org/10.22617/TCS200199-2</bib>
<bib id="bib6"><number>[6]</number>Nidya Chitraningrum, Lies Banowati, Dina Herdiana, Budi Mulyati, Indra Sakti, Ahmad Fudholi, Huzair Saputra, Salman Farishi, Kahlil Muchtar, and Agus Andria. 2024. Comparison Study of Corn Leaf Disease Detection Based on Deep Learning YOLO-v5 and YOLO-v8. J. Eng. Technol. Sci., 56(1), 61-70.DOI: https://doi.org/10.5614/j.eng.technol.sci.2024.56.1.5</bib>
<bib id="bib7"><number>[7]</number>Ayyoub Bouhayane, Zakaria Charouh, Mounir Ghogho, and Zouhair Guennoun. 2023. A Swin Transformer-based Approach for Motorcycle Helmet Detection. IEEE Access, vol. 11, pp. 74410-74419. DOI: https://doi.org/10.1109/ACCESS.2023.3296309</bib>
<bib id="bib8"><number>[8]</number>Adekanmi Adeyinka Adegun, Jean Vincent Fonou Dombeu, Serestina Viriri, and John Odindi. 2023. State-Of-The-Art Deep Learning Methods for Objects Detection in Remote Sensing Satellite Images. Sensors 2023, 23(13), 5849. DOI: https://doi.org/10.3390/s23135849</bib>
<bib id="bib9"><number>[9]</number>Statista. 2023. Number of registered private motorcycles and tricycles in the Philippines from 2020 to 2022. Retrieved from https://www.statista.com/statistics/708054/number-of-registered-private-motorcycles-and-tricycles-in-the-philippines/</bib>
<bib id="bib10"><number>[10]</number>Republic of the Philippines. (2010). Republic Act No. 10054, An Act Mandating All Motorcycle Riders to Wear Standard Protective Motorcycle Helmets While Driving and Providing Penalties Therefor. Congress of the Philippines</bib>
<bib id="bib11"><number>[11]</number>Rosemary Seva. 2017. Modeling Motorcycle Accident Severity in the Philippines Using Helmet Use, Riding Experience, and Driving Behaviour. International Journal for Traffic and Transport Engineering, 7(3), 342-353. DOI: https://doi.org/10.7708/ijtte.2017.7(3).05</bib>