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Mask Detection on Motorcyclists Using YOLOv4

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Abstract−The use of mask is a mandatory for everyone in the pandemic regulation to prevent the spread of COVID-19 infection. This becomes a pandemic regulation for everyone, especially in public places like in traffic situation, such as pedestrian and motorcyclists. However, many motorcyclists ignore this rule or do not use the mask properly, let alone they have high risk in being infected by the virus; Thus, a computer vision-based solution is required to help monitoring it. This study aims to build a system to automatically detect the use of mask on motorcyclists. Here, we propose a YOLOv4 model, one of YOLO variants, which is popular in the object detection task and featured with a considerably high speed in real-time situation. This study also implements domain adaptation to discuss the object detection performances. Based on the experimental results in various scenarios, our model obtained average accuracy of 78.3% and IoU of 64.8% for class with_mask, average accuracy of 78.4% and IoU of 56.3% for class without_mask, and average accuracy of 87% and IoU of 55.5% for class incorrect_mask.

Keywords: COVID-19; Mask; Detection; Motorcyclist; YOLOv4

1. INTRODUCTION

Coronavirus disease (COVID-19) was discovered in December 2019 and was first reported by the Wuhan municipal government in China[1]. The transmission of the COVID-19 virus has a very fast transmission speed, because the virus can be transmitted by droplets [2]. The World Health Organization (WHO) officially declared the outbreak of COVID-19 a global pandemic in March 2020. According to Worldometer data as of April 18, 2022, the number of positive cases of the COVID-19 virus has reached about 504 million people, of which about 6.2 million people have died, and about 456 million people have been declared cured of the virus.

During the pandemic, the use of masks is one of the things that must be carried out in various places, such as the regulation that has been decided by the Minister of Health of the Republic of Indonesia Number HK.01.07/MENKES/382/2020 which explains the Health Protocol for the Community in Public Places and Facilities in Order of Prevention and Control of Corona Virus Disease 2019 [3]. This is done to prevent the spread of the COVID-19 virus, because masks can hold droplets released from a person's mouth when talking, sneezing, and coughing in public places. In addition, the spread of the COVID-19 virus can occur in various closed and open places that are often visited by the public. The highway is one of the places that can become a place for the spread of COVID-19, this happens because there are still many people who drive without complying with the health protocols set by the government. Therefore, a system is needed to detect the use of masks on motorcyclists on the highway to help officers to reduce the spread of the COVID-19 virus.

There are several methods that can be used to detect the use of masks on motorcyclists, one of which is YOLO. YOLO is known as the fastest identification method with high accuracy in detecting objects or face recognition. In a study conducted by Giancini et al, regarding the use of YOLOv4 on human detection [4], the accuracy of this study is 87.03%.

Study on object detection using YOLO has been previously conducted by Bagus et al, regarding the detection system of motorcyclists without helmets and excess passengers [5]. The accuracy of this study is 84.6% with 173 training images. Another study regarding helmet detection on motorcyclists conducted by Albert et al [6] had 70.49% accuracy using Convolutional Neural Network (CNN) and YOLO.

In a study conducted by Anarki et al, regarding face mask detection [7]. This study had the highest accuracy of 88.7% using Haar Cascade. Another study on object detection with the mask as an object also has been previously conducted by Putri et al [8] using CNN. The accuracy of this study is 99% with 2000 dataset images. Another study has been conducted by Adusumalli et al, on face mask detection [9]. This study accomplished an overall efficiency of 97%. Another study on face mask detection has been previously conducted by Ding et al [10] using RCNN, accomplished accuracy of 97%.

Some of the papers above stated that the use of YOLO model has good performance in detecting objects. In addition, the papers above regarding mask detection using other methods has good performance in detecting. However, some of aforementioned papers have not detecting mask using YOLOv4 model and have not implement the domain adaptation for detecting mask on motorcyclist.

In this study, we propose mask detection system on motorcyclists, in order to help reducing the spread of the COVID-19 virus during a pandemic. It is hoped that this study's results can help officers monitor motorcyclists who comply with one of the health protocols by wearing masks or not. And also, we hoped that this study can be a way to increase public awareness of the importance of using health protocols in life during a pandemic.

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With the problem regarding detecting the use of the mask, this research focuses on implementing YOLO to detect the use of the mask on motorcyclists. The author's implementation uses the YOLOv4 modeling algorithm. Domain adaptation is also used in this study to ensure the dataset trained as the source domain can work well on the images of motorcyclists in various conditions as a target domain.

In summary, our contributions in this paper are as follows: (a) We implement YOLOv4 model and perform domain adaptation to detect masks on motorcyclists using a model trained with person-in-general or pedestrian domain; (b) We conducted experiments on various scenarios, including crowded, non-crowded, raining, and night.

The rest of this paper discusses methodology used and related works in this research. Section 3 explains the experimental results and discussion. Finally, Section 4 gives the concluding remarks of the paper.

2. RESEARCH METHODOLOGY

2.1 Overview

The system built in this study is a system for detecting the use of masks on motorbike riders using YOLOv4. An overview of the system is shown in Figure 1.

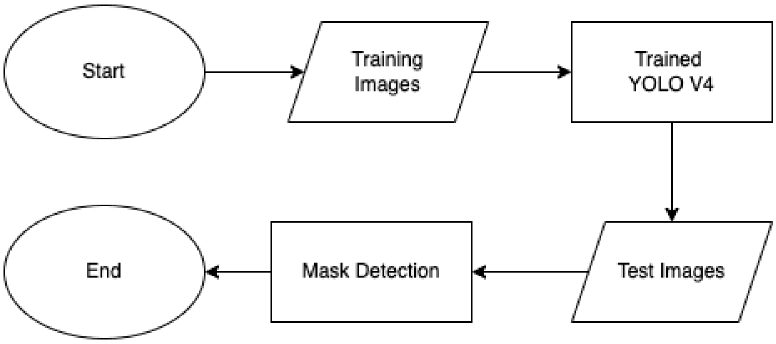

Figure 1. System Design Flowchart

2.2 Training

Training is a process of the data trained using the YOLOv4 model which produced new weights that are used in the mask detection process to recognize the object. The result of this process is a YOLOv4 -trained model to test the use of masks in the testing images.

2.3 Testing

Testing is the process where the model that has been trained using the training dataset can work well on testing images results to be evaluated. Testing records will be distinguished based on *with_mask*, *without_mask*, and *incorrect_mask* classes. An overview of the testing process system is shown in Figure 2.

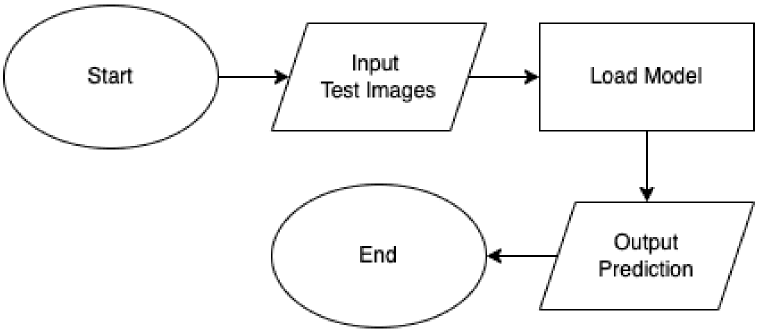

Figure 2. Flowchart Testing

2.4 Evaluation

At this stage, the evaluation metrics are used as a determinant of the score of the mask detection using the YOLOv4 model. In Table 1 can be seen some of the variables of the metrics.

Table 1. Confusion Matrix

	Actual Positive Class	True Negative Class
Predicted Positive Class	True Positive (TP)	False Negative (FN)
Predicted Negative Class	False Positive (FP)	True Negative (TN)

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Some of the metrics used are:

a. Accuracy

Accuracy is a measurement level of the correct ratio. Accuracy can be calculated using equation (1) [11].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

b. Precision

Precision is a comparison of the amount of data categorized as positive and correctly predicted by the system with the total amount of positive predicted data. Precision can be calculated using equation (2) [11]

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

c. Recall

Recall is a measurement of data with a true positive classification and can be calculated using equation (3) [12].

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

d. F1-Score

F1-Score is a combination calculation method of precision and recall. F1-Score can be calculated using equation (4) [12].

$$F1 - Score = 2 \times \frac{Precision\ \times Recall}{Precison + Recall} \tag{4}$$

e. Intersection Over Union (IoU)

IoU is a metric used to evaluate the accuracy of a system in detecting an object on a trained dataset [13]. The IoU compares the GT bounding box with the prediction bounding box from a model [14]. If A is the image of the motorcyclists and B is the image of the detection result, then IoU can be calculated by equation (5).

$$IoU = \frac{A\ \cap\ B}{A\ \cup\ B} \tag{5}$$

2.5 You Only Look Once (YOLO)

YOLO is an object detection algorithm that works in real-time [15]. The detection system implemented with this method consists of using a repurpose classifier or localizer for detection. Models are applied to images at various locations and scales. The area with the highest score in the image will be considered a detection [16].

YOLO divides the $S \times S$ size image, where S is a variable that has a value of 7, and the input image size is 448 x 448. If the coordinate center is on the Ground Truth (GT), then there is an object in the grid and it is the responsibility of the grid to detect it. Each cell predicts a bounding box B with a confidence value for containing the object and its prediction accuracy for the probability of the object inside the bounding box[17]. The input image is convolved to get a predicted bounding box, and the final result is a bounding box of size $S \times S \times (B * 5 + C)$ where the value B is the number of bounding boxes in 1 grid, and C is the number of categories classification can become. The bounding box has 5 values which are x-coordinate, y-coordinate, width, height, and confidence value [18].

Each attribute contained in the bounding will be normalized so that it has a value between 0 and 1. The x and y coordinates are normalized based on the top left point of the grid, while the height and width will be normalized according to the size of the image[18]. It can be seen in Figure 3 is an example of the YOLO algorithm method.

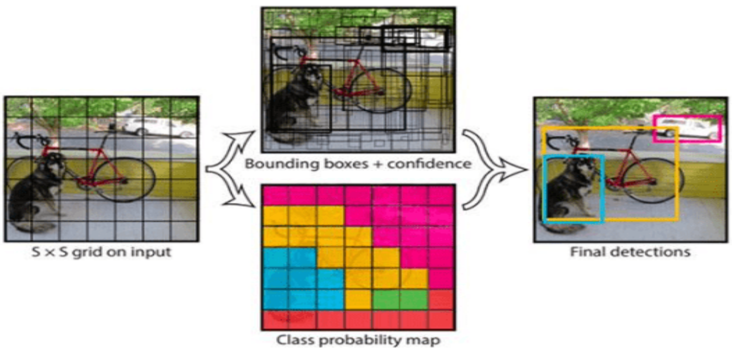

Figure 3. YOLO Algorithm Method [15]

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YOLOv1 proposed to detect the target through the grid divide and identify targets by the location of the target center on the grid. YOLOv2 detects objects using multi-scale feature maps based on SSD and passes through the layer to link proposed high-resolution feature maps with low-resolution feature maps to enable multi-scale detection. While, YOLOv3 has made two improvements on its basis YOLOv2. One is to continue to use the residual model to deepen the network structure; the other is to use FPN Architecture for multi-scale detection [19].

YOLOv4 algorithm has been significantly modified from previous versions and has significantly improved accuracy [20]. YOLOv4 improves two important parameters for evaluating the quality of object detection algorithms, namely: accuracy (average precision/AP) and speed (frames per second/FPS). Additionally, model training can be performed on a single GPU. There are technical specifications for repairing the network, namely bag-of-freebies and bag-of-specials. Using CSPDarknet53 on YOLOv4 as the backbone of the feature extraction architecture. Compared to other tear detectors such as EfficientDet, YOLOv4 works twice as fast, while YOLOv3 improves AP and FPS by 10% and 12%, respectively[21].

2.6 Domain Adaptation

Domain adaptation consists of learning from data in the source domain and limited information in the target domain to create a good working model for the target domain. A well-studied direction is unsupervised image classification. Given an image of an identified source domain and an image of an unidentified target domain, the goal is to obtain a classifier for the target domain [22]. In this study, domain adaptation was implemented in detecting the use of masks on motorbike riders with data that had previously been trained in the form of a dataset with the use of masks in crowds and non-crowds.

3. RESULT AND DISCUSSION

In this study, training and testing were carried out to obtain the performance of mask detection on motorcyclists using the YOLOv4 model. In the testing section, the domain adaptation was carried out to test the model that has been trained on the test data as the target domains. The test data carried out in this trial is divided into various scenarios.

3.1 Dataset

The dataset used in this study consists of the use of masks in a crowded. The dataset used for training consists of 848 images obtained from “Face Mask Detection” [23]. This dataset is divided by the ratio of 80% data training : 20% data validation. For testing data we collected 40 images arbitrarily, mixed from internet; The images were in various conditions. We manually annotated the testing images using a conventional annotation tool (https://www.makesense.io/). Table 2 shows the amount of combined dataset used in this study.

Table 2. Dataset

Data	Images Total
Training	680
Validation	168
Testing	40

Figure 4. Samples of Dataset

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In Figure 4 can be seen the dataset used for training. The dataset consists of various conditions of use such as crowded and non-crowded conditions. This mask dataset will be divided into 3 classes, namely: *with_mask*, *without_mask*, and *incorrect_mask*. Meanwhile, the samples of data tests can be seen in Figure 5.

(a) (b) (c) (d)

Figure 5. Samples of Data Test

This data tests consists of various conditions, such as (a) crowded, (b) non-crowded, (c) rainy, and (d) night. Each condition in this test image consists of motorcyclists. The motorcyclists will be detected whether the riders belong to the class *with_mask*, class *without_mask*, or class *incorrect_mask*.

3.2 Results of Training YOLOv4 for Detection of The Use of Masks on Motorcyclists

In this process, training is carried out with the aim that the image contained in the dataset finds a correlation between the use of masks and not in the dataset. During this training phase, the training process can be stopped if the average loss value decreases with each iteration. Based on the training process that was carried out with a total of 2000 iterations, and the average of accuracy in this training process is 78.82% and average IoU of 71.70%. The detection results on the validation dataset in this training process are shown in Table 3.

Table 3. Detection Results on The Validation Dataset

	Avg Accuracy	Precision	Recall	F1-Score	Avg IoU
Results	78.82%	88%	89%	89%	71.70%

3.3 Results of Testing Process YOLOv4 for Detection of The Use of Masks on Motorcyclists

This section performs mask detection with a model that has been trained using a dataset consisting of 848 images with crowded and non-crowded training and validation data conditions. Domain adaptation is performed in this section to ensure that the system that has been created using the training data can work properly in the target domain. The detection results is divided into three class, sometimes in each test samples contains class *with_mask*, or sometimes contains class *without_mask*, or sometimes contains class *incorrect_mask*, and sometimes it contains the combination of them. The results of the testing system are taken based on the average accuracy and average IoU of each class in each sample tests.

The target domain in this study is divided into various scenarios with a total of 40 images, including:

a. **Non-crowded riders**, in this scenario consists of no more than 5 motorcyclists.
b. **Crowded riders**, in this scenario consists of more than 5 motorcyclists.
c. **Raining**, in this scenario is carried out in rainy conditions which consist of motorcyclists.
d. **Night**, in this scenario is carried out in night conditions which consist of motorcyclists.

3.3.1 Non-Crowded Scenario

The first test was carried out on motorcyclists who were not in a crowd with 10 data tests. The results of the test can be seen in Figure 6.

Figure 6. Results of Non-Crowded Scenario Tests

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In Table 4, it can be seen that testing in this scenario has good results in detecting class *with_mask* which has an average of 90.1% accuracy and IoU of 68.4%. However, it can be seen in trial number 6, that the accuracy obtained was 70.5% and IoU of 39%, this happened because the greater the detection results, could reduce the area of the prediction bounding box resulting in a smaller IoU. Class *without_mask* gets an average accuracy of 74.8% and IoU of 58.2%, while class *incorrect_mask* only has one detection with an average accuracy of 98% and IoU of 66%.

Table 4. Results of Non-Crowded Scenario Tests

Testing Number	Class					
	with_mask		*without_mask*		*incorrect_mask*	
	Average Accuracy	**Average IoU**	**Average Accuracy**	**Average IoU**	**Average Accuracy**	**Average IoU**
1	100%	69%	-	-	-	-
2	87%	81%	-	-	-	-
3	99%	80%	84%	60%	-	-
4	99%	82%	98%	88%	-	-
5	60.5%	53%	-	-	98%	66%
6	70.5%	39%	49%	34%	-	-
7	99%	70%	98%	72%	-	-
8	88%	45%	45%	37%	-	-
9	100%	84%	-	-	-	-
10	98%	81%	-	-	-	-
Total Avg	**90.1%**	**68.4%**	**74.8%**	**58.2%**	**98%**	**66%**

3.3.2 Crowded Scenario

The second test was carried out on motorcyclists who were in a crowd with 10 data tests. The results of the test can be seen in Figure 7.

Figure 7. Results of Crowded Scenario Tests

In Table 5, it can be seen that testing in this scenario has quite good results, namely with an average accuracy of 82.87% and IoU of 63.6% for class *with_mask*, average accuracy of 92.95% and IoU of 59% for class *without_mask*. However, it can be seen on class *without_mask* the IoU value is much smaller than the accuracy value because the more specific the object detected, the prediction bounding box area smaller, and resulting the IoU smaller. Whereas, class *incorrect_mask* only has one detection with an average accuracy of 76% and IoU of 45%. In this scenario, several other motorbike riders cannot be detected because they are blocked by other motorbike riders, and the image quality and the distance of the motorcycle in the image affect the detection results.

Table 5. Results of Crowded Scenario Tests

Testing Number	Class					
	with_mask		*without_mask*		*incorrect_mask*	
	Average Accuracy	**Average IoU**	**Average Accuracy**	**Average IoU**	**Average Accuracy**	**Average IoU**

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1	96.4%	80%	-	-	-	-
2	88.5%	70%	93.5%	57%	-	-
3	69.1%	55%	-	-	-	-
4	93%	60%	92.4%	61%	-	-
5	65%	60%	-	-	-	-
6	91.8%	62%	-	-	76%	45%
7	97.5%	74%	-	-	-	-
8	73%	41%	-	-	-	-
9	72.2%	64%	-	-	-	-
10	82.2%	70%	-	-	-	-
Total Avg	**82.87%**	**63.6%**	**92.95%**	**59%**	**76%**	**45%**

3.3.3 Raining Scenario

The third test was carried out on motorcyclists who were in rainy conditions with 10 data tests. The results of the test can be seen in Figure 8.

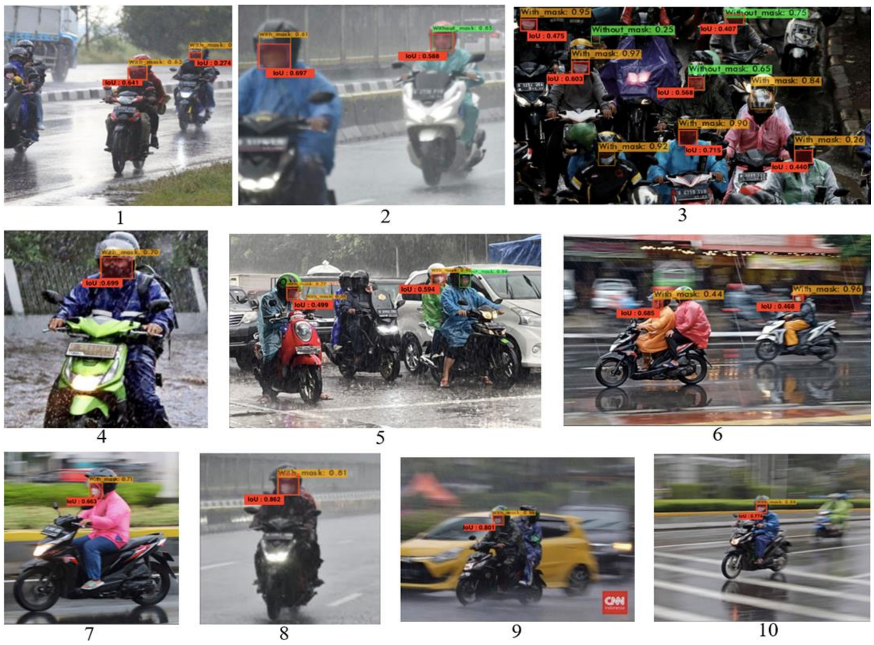

Figure 8. Results of Raining Scenario Tests

In Table 6, can be seen that testing in this scenario has quite good results in detecting class *with_mask*, which has an average accuracy of 61% and IoU of 54.8%. In this detection, there are several results of class *without_mask* detection in several tests, the results obtained in this class are quite good, namely with an average accuracy of 77.5% and IoU of 53%. In this scenario trial, the accuracy and IoU values were small because they were affected by rainy conditions which caused the image condition to be less clear. Meanwhile, class *incorrect_mask* cannot be detected, because no motorcyclist were detected in that class.

Table 6. Results of Raining Scenario Tests

Testing Number	Class					
	with_mask		*without_mask*		*incorrect_mask*	
	Average Accuracy	Average IoU	Average Accuracy	Average IoU	Average Accuracy	Average IoU
1	37.6%	30%	-	-	-	-
2	61%	69%	85%	58%	-	-
3	51%	37%	70%	48%	-	-
4	70%	69%	-	-	-	-
5	57.3%	36%	-	-	-	-
6	46%	38%	-	-	-	-
7	71%	66%	-	-	-	-
8	81%	86%	-	-	-	-
9	48%	40%	-	-	-	-
10	88%	77%	-	-	-	-
Total Avg	**61%**	**54.8%**	**77.5%**	**53%**	**-**	**-**

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3.3.4 Night Scenario

The fourth test was carried out on motorcyclists who were in a night condition with 10 data tests. The results of the test can be seen in Figure 9.

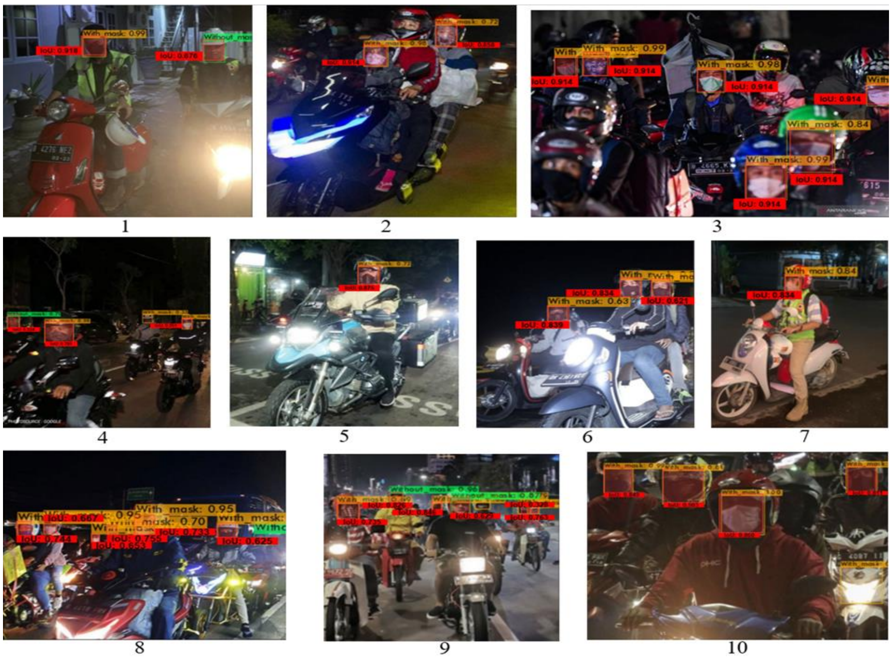

Figure 9. Example Results of Night Scenario Tests

In Table 7, it can be seen that testing in this scenario has quite good results in detecting class *with_mask* which has an average accuracy of 79.4% and IoU of 72.4%, it can be seen in test number 4 that there are detection results with average accuracy of 35.5% and IoU of 26% for class *without_mask*, this happens because the quality of light, image quality, and the distance of the motorcyclists affects this detection. In this detection scenario, several detection results in the class *without_mask* produce an average accuracy of 68.5% and an IoU of 55%. Meanwhile, in class *incorrect_mask*, nothing was detected because no motorcyclist were detected in that class.

Table 7. Results of Night Scenario Tests

Testing Number	**Class**					
	with_mask		***without_mask***		***incorrect_mask***	
	Average Accuracy	**Average IoU**	**Average Accuracy**	**Average IoU**	**Average Accuracy**	**Average IoU**
1	99%	91%	92%	67%	-	-
2	85%	85%	-	-	-	-
3	81.7%	67%	-	-	-	-
4	98%	67%	35.5%	26%	-	-
5	72%	75%	-	-	-	-
6	80.6%	76%	-	-	-	-
7	84%	83%	-	-	-	-
8	65%	59%	-	-	-	-
9	55%	53%	78%	72%	-	-
10	73.6%	68%	-	-	-	-
Total Avg	**79.4%**	**72.4%**	**68.5%**	**55%**	**-**	**-**

3.4 Discussion

After carried out the detection process, the use of the masks was carried out in several tests. The results of testing this system are taken based on the average of each class in each trial. The highest average results of the testing detection trial of class *with_mask* on motorcyclists were in the non-crowded scenario with an average accuracy of 90.1% and IoU of 68.4%, whereas the lowest average results were in the class *with_mask* in the raining scenario with an average accuracy of 61% and IoU of 54.8%. This detection of masks in motorcyclists is also affected by the light conditions, image conditions, and motorcycle distance. Also, the comparison of a large accuracy value and small IoU value affected by the detection results which are more specific so that it produced a smaller bounding box and produced a smaller IoU.

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4. CONCLUSION

Based on the experimental result, this system was built with the YOLOv4 algorithm to detect the use of masks on motorcyclists. This research also implements domain adaptation to test that the training dataset in the form of mask users in crowded and non-crowded conditions that have been trained can be implemented on motorcyclists. This research uses 40 tests consisting of various motorcyclist conditions, crowded conditions, non-crowded conditions, rainy conditions, and night conditions. In this study, it can be concluded that this mask detection system is good at detecting motorcyclists. This study obtained an average accuracy of 78.3% and IoU of 64.8% for class *with_mask*, then average accuracy of 78.4% and 56.3% of IoU for class *without_mask*, and average accuracy of 87% and 55.5% of IoU for class *incorrect_mask*.

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