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Geometry and Color Transformation Data Augmentation for YOLOV8 in Beverage Waste Detection

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ABSTRACT

In the bottle sorting process in real world, there are some beverage packaging waste that is deformed. Deformed objects can result in detection errors by an object detection system. Detection errors can also occur in attributes that share similar feature maps. Detection errors can be caused by models that are unable to generalize to the data. Several methods have been devised to prevent such issues, with data augmentation being one of them. To increase the variety of data, data enhancement techniques will be utilized. This research employs a data augmentation technique that concentrates on geometry transformations such as scaling and rotation, as well as color transformations such as hue, saturation, and brightness. Additionally, a combination of geometry and color transformations was conducted, resulting in a total of 39 experimental scenarios. This study demonstrates that data augmentation can affect the model's performance in terms of accuracy and the number of detection results. The combined method of scaling and rotation, which is applied to the original data, reveals the optimal experimental scenario with an accuracy of 88.4%.

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1. INTRODUCTION

In the actual bottle sorting process, some beverage packaging waste items, such as cans and plastic bottles, are deformed or have changed shape. Objects that have been deformed can result in system detection errors. Errors in detection can also occur with characteristics that share similar feature maps, such as plastic and glass bottles. The system can identify objects as identical. Models that are unable to generalize well to the data can result in detection errors (Thanapol, P., 2020). This can be caused by a dataset with insufficient variation.

In the application of deep learning, particularly CNN (Convolutional Neural Networks), a common issue is the lack of dataset variation. These conditions are common in deep learning algorithms or models in which the resultant model is too complex to accurately predict testing data or other data that was not used during training but performs well with training data (Zhang, H., et al, 2019). Several methods, such as the early stopping method, network reduction method, regularization method, and data augmentation method (Ying, X, 2019) have been devised to prevent this problem in models.

In this study, the data augmentation technique will be used to increase the variety of deformed data with similar feature map characteristics. This method of augmenting data is expected to make the model more optimal and generalizable. This research employs a data augmentation technique that concentrates on geometry transformations such as scaling and rotation, as well as color transformations such as hue, saturation, and brightness.

Object detection can be used to aid the process of detecting beverage packaging waste in a bottle sorter system. This research will utilize YOLO (You Only Look Once) as a model for an object detection algorithm. YOLO is a regression-based method, also known as a single-stage detector, that defines the class by mapping the object region directly from the value pixels (Soviany, P, 2018). In this study, the YOLOv8 model is proposed as the object detection model; its YOLO version is state-of-the-art.

The objective of this study is to determine the optimal and best performance of the YOLOV8 model for detecting beverage packaging waste using the data augmentation method, which combines geometry and color transformation. Then, the number of detection results and evaluation metrics consisting of AP, mAP, recall, and precision are used to assess the model's performance.

2. LITERATURE REVIEW

2.1 Beverage Waste

Beverage packaging waste is a type of waste generated from packaging or containers used for liquid beverages. Cans and bottles are examples of beverage packaging waste. A bottle is a liquid vessel or bottle that usually has a neck that is narrower than the body. Just like bottles, cans are a storage or container, but made of metal or aluminum.

Figure 1. *Beverages Waste Images*

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2.2 Deep Learning

Deep Learning (also known as deep structured learning or hierarchical learning) is learning a representation of existing data, rather than a specific algorithm. Deep Learning is a subset of machine learning algorithms which: (1) uses multiple layers of non-linear processing units sequentially for feature extraction and feature transformation. Each subsequent layer uses the output of the previous layer as input, (2) learns multiple levels of representation corresponding to different levels of abstraction. There are two different types of neural networks. Networks that only consist of input layers and output layers are called single-layer neural networks. Meanwhile, a network that consists of an input layer, hidden layer, and output layer is called a multi-layer neural network. Then, a network consisting of only one hidden layer is called a shallow neural network, while a network consisting of two or more hidden layers is called a Deep Neural Network (DNN) (Kim, P., 2017).

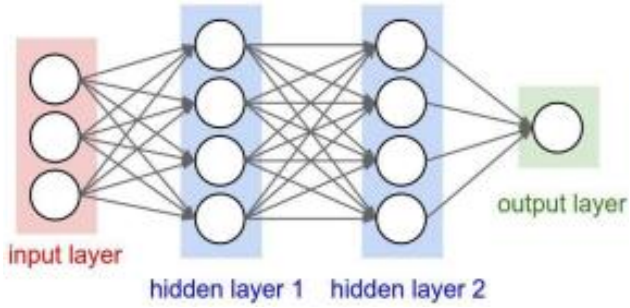

Figure 2. Neural Network Layer

Deep Learning plays an important part in object detection as the neural networks used can handle very large and complex data. In object detection, deep learning is used in three main stages, namely: edge detection, feature detection and object detection. There are two main procedures involved in deep learning models, namely forward propagation, and backward propagation (Unita., 2018).

2.3 Convolutional Neural Netwrok

CNN (Convolutional Neural Network) is a type of Deep Learning model used to process data that has a grid structure, such as images and videos. It is designed to understand the spatial hierarchy of features (Yamashita, 2019). CNN is very efficient for image processing because a feature can appear anywhere in the image. Compared to traditional machine learning models, CNN has advantages in terms of feature expression and feature learning. Based on its use with deep learning algorithms, CNN models have been widely applied to computer vision fields, such as image classification, object detection, and segmentation (Wang, et. al, 2019). CNN architecture has a hierarchical network, with multiple layers and each layer consists of a stack of convolutional kernels that perform various computations and conversions (Patel, R 2020).

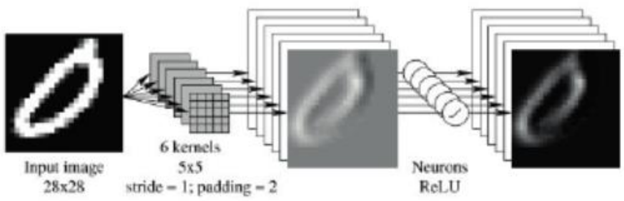

Figure 3. Convolution Layer

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2.4 Object Detection

Object Detection is a method to determine the location of an object in an image and classify the object into a more specific class. The detected object is annotated in the form of a bounding box to mark the presence and location of an object (Zhao, Z., et al, 2019) then the object is classified into a certain class with the aim of recognizing the object (Deepan, P, et al, 2020). There are two types of methods in object detection, namely: regression-based methods and region proposal-based methods. In this research, object detection is used to detect the type of beverage packaging waste and can be classified correctly into 3 classes. The object detection method used in this research is YOLOV8 model.

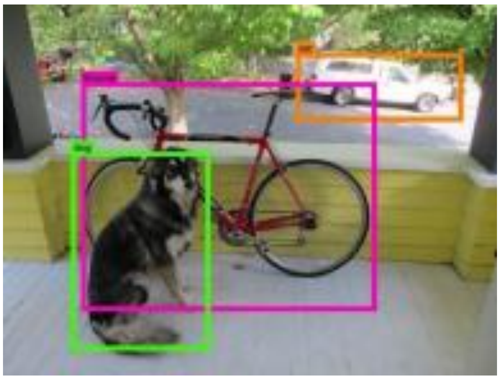

Figure 4. Object Detection YOLO Ilustration

2.5 YOLO V8

YOLO is an object detection model that uses a single convolutional network to simultaneously predict straight from the pixels in the images or videos to the coordinates of the bounding box and determine the probability of a class (Redmon, et al, 2015). YOLOV8 is one of the latest versions of YOLO model that can also perform image classification and segmentation (Solewatz). YOLOV8 was developed by Ultralytics who also created the model from the YOLOV5 version in 2021, where this model has been widely influential in the industry.

YOLOV8 was developed to be fast, precise, and easy to use for various types of image segmentation and object detection (Ultralytics, 2023). The YOLOV8 model builds on the success of previous versions of the YOLO model and adds new features to improve performance and flexibility, including several changes and architectural improvements from previous versions of the model, YOLOV5.

2.6 Hyperparameter

Hyperparameters are parameters used to configure models in machine learning, such as epoch, learning rate and batch size in training a neural network or determining the algorithm used to minimize the occurrence of loss functions (Nyuytiyimbiy, 2020). The hyperparameter model value is determined before the model starts training. The speed and accuracy of the model training process is affected by hyperparameters. The number of hyperparameters required by a model varies.

Learning Rate is the amount of change that occurs in the model at each iteration while searching for the model, or the size of each stage (Brownlee, 2019). Batch Size is the number

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of samples used to calculate the gradient of the error before changing the parameters of the model (Brownlee, 2019). Epoch refers to the number of rounds or trajectories travelled by the model during the training process, with all datasets available before the training process is stopped (Brownlee, 2019).

2.7 Perfomance Matrix

The object detection model performance evaluation method that will be used in this research is accuracy (mAP). Mean Average Precision (mAP) is a measurement matrix used to evaluate object detection models such as Fast R-CNN, YOLO, Mask R-CNN. Mean Average Precision has a value between 1 and 0. Mean Average Precision is one of the derivatives of Average Precision (AP) which represents the average of AP values in retrieving information on a set of n classes. Mean Average Precision has a formula consisting of several sub matrices, namely: Confusion Matrix, Intersection over Union (IoU), Recall and Precision (Shah, D., 2022).

$$mAP = \frac{1}{n} \sum_n AP_n \quad (1)$$

$$\boldsymbol{R} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \quad (2)$$

$$\boldsymbol{P} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \quad (3)$$

Equation 1 shows the formula for calculating mAP, while equations 2 and 3 are used for calculating the recall and precision. Confusion Matrix is a matrix table that describes the classification performance of the designed object detection model on a set of test data whose true values are known. Intersection over Union (IoU) is a jaccard index-based measurement matrix used to compare the similarity between two forms.

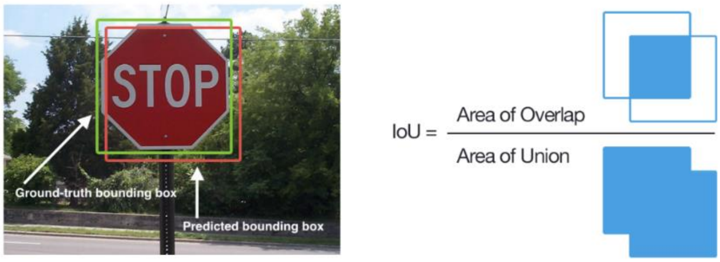

Figure 5. Intersection over Union

Recall is a matrix used in the information retrieval domain to measure how good an information retrieval system is. Then, the recall matrix calculates the number of correct positive classification results out of all positive classification results [20] an d precision is the same matrix as recall, which measures the application ability to retrieve relevant documents according to the user's request (Zeugmann, 2011).

2.8 Data Augmentation

Data augmentation is a strategy that allows practitioners to significantly increase the diversity of data available for training models, without collecting new data (Ho, D, 2019). In its application, there are two data augmentation techniques used, namely: warping techniques and oversampling techniques (Shorten, et al, 2019).

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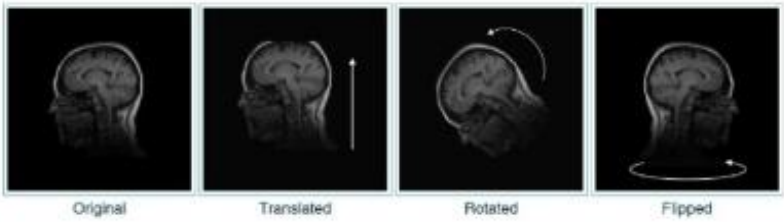

Figure 6. Data Augmetation Example

In this research, the augmentation methods used are warping techniques which contain geometry transformation such as scaling, rotation and color transformation such as hue, saturation, brightness. The following sentences is a brief explanation of the geometry transformation augmentation methods and techniques used in this research.

1) Scaling

Scaling is to increase or decrease the size of an image with a certain scale value (Lei, C, et al, 2019). Figure 7 shows the original image and the results after scaling with a scale value twice the magnification of the original size.

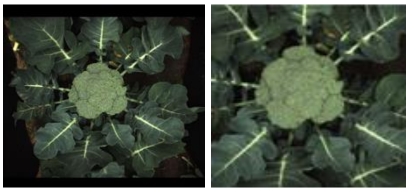

Figure 7. Image Before and After Scaling

2) Rotation

Rotation method rotates the image at an angle with a certain degree (Yang, S., Xiao, 2022). The degree of rotation ranges is from 1° to 359°. If the value is negative, then the rotation direction occurs clockwise. The following is an example of an image before and after rotation with values between 0° to 90°.

Figure 8 Image Before and After Rotate

3) Color Jitter

Color Jitter is changing or adjusting channel values in image colors, as used in this research, including hue and saturation, and changing the contrast or brightness to a certain value (Howard, J, 2020). The following is an explanation of the type of color jitter used in the research.

a) Hue

Hue refers to the pure intensity of the base color, or the visible spectrum of the basic color [25].

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b) Saturation

Saturation is the level of density and intensity of the colors that appear in an image (Chin, J. 2021). The higher the value of saturation, the clearer and sharper the color will be.

c) Brightness

Brightness is the relative brightness or darkness of the pixels in an image. The brightness can range from black (no brightness) to white (maximum brightness). Increasing the brightness value will make each pixel in the image appear brighter (Hasty. 2023).

Figure 9. Image with Data Augmentation Color Jitter

3. METHODS

3.1 Dataset

The data that will be used in this research is a collection of beverage packaging waste data. The data is sourced from the Kaggle website. The data obtained from the Kaggle website have been distributed so that the data will be balanced in each class, the data divided based on object shape characteristics. The amount of data used in this research is 750 image data with 3 classes of beverage packaging waste types that are commonly known such as plastic bottles, cans, glass bottles.

Table 1. Amount of Data for Each Class

Type of Beverage Waste	Amount
Plastic Bottle	250
Can	250
Glass Bottle	250
Total	**750**

3.2 Methodology

There are several steps in conducting research methodology as shown in Figure 10.

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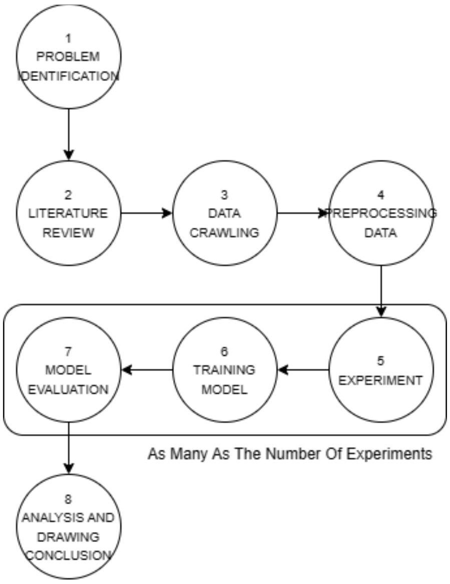

Figure 10. Research Methodology

1) Problem Identification

There are two main problems in beverage packaging waste detection. First, the deformation of the shape of the beverage packaging waste (plastic and can waste types). Second, the similarity of feature maps (such as color, shape and size).

These detection errors occur because the model is not good at generalizing data due to lack of data variance. Data augmentation can be a solution, especially how to add deformed waste and waste with similar feature maps.

2) Literature Review

The literature review is a phase of searching and learning about various sources of literature needed in order to gain knowledge and information related to the concepts and methods used in this research. Literature can be obtained through journals, books, and articles from credible websites.

3) Data Crawling

The amount of data used in this research is 750 image data with 3 classes of beverage packaging waste types such as plastic bottles, cans, glass bottles. The image data obtained comes from several sources on the Kaggle website. Data is also grouped into 2 types of data, into deformed data and original data.

Table 2. Amount of Data for Each Sources

Data Source	Original Data	Deformed Data	Amount
TACO	140	31	171
Garbage Classification	142	38	180
Bottle Cans Images	9	11	20
Drinking Waste Classification	104	25	129
Alcohol Bottle Images	81	0	81
Others	142	27	169
Total	**618**	**132**	**750**

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4) Preprocessing Data

Preprocessing data is the process of cleaning, organizing, and adjusting data so that the data used is more optimal when used in the training process (Muttaqin, F, 2020). In this research, data preprocessing is carried out because there are some image data with the location or position of objects in the image that are not perfect, such as objects that are cut off or objects that are too small with large and complex backgrounds.

One type of preprocessing data that carried out in this research is the cropping and changing background technique. Cropping is done on image data that has a small object but the background on the object is large and complex, so the image is cropped so that the object is clearly visible, this can also help YOLO detect objects during training.

Figure 11. Before and After Cropping Technique

Then, the next data preprocessing step is to change the background of the image into black color. This aims to make the data used relevant to the application case study on the bottle sorter tool, which uses a conveyor belt with a black or gray background. In addition, changing the background can eliminate complex objects in the image, which are not needed so that they can affect the model in the image data training process.

5) Experiment

In this research, experiments were performed on the implementation of data augmentation processes and their combinations. The implementation of data augmentation includes geometric transformations such as rotation, scaling and color transformations such as hue, saturation, brightness which become part of the color jitter.

6) Model Evaluation

This step is analysis and evaluation of all results experiments that have been run. Experiment refers to the experimental scenario, which is where all experimental results will be compared starting from baseline to a combination of the three data augmentation methods. The detection results produced by the baseline are used as a research reference to measure the performance of the resulting model compared to the other experiment. From the results of this analysis, it will be seen which model performance is the best from the experimental results.

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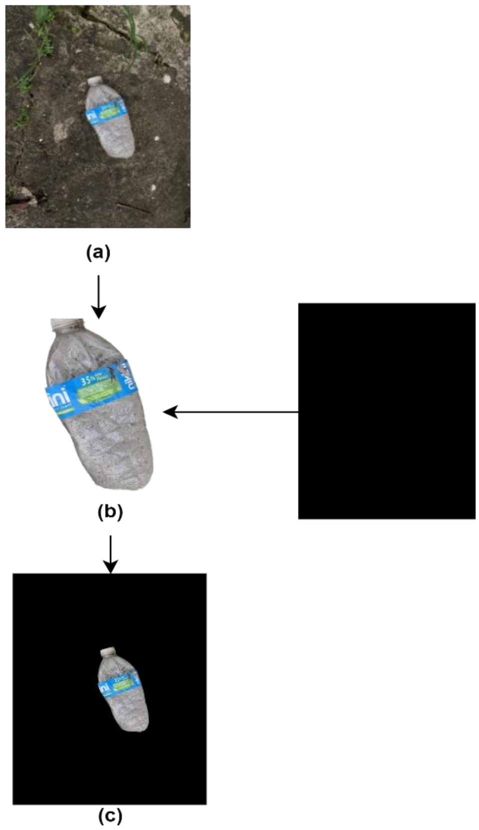

Figure 12. Changing Background Technique

Table 3. Scenario Experiment

ID	Implementation of Data Augmentation
1.1	Baseline (Original)
1.2	Baseline (Deformed)
1.3	Scaling (Mean)
1.4	Scaling (Median)
1.5	Rotation (90)
1.6	Rotation (135)
1.7	Rotation (225)
1.8	Rotation (270)
1.9	Scaling (Mean) + (Median)
1.10	Rotation (90) + (225)
1.11	Rotation (135) + (270)
1.12	Rotation + Scaling
1.13	Baseline (Color)
1.14	Hue
1.15	Saturation
1.16	Brightness

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1.17	Hue + Saturation
1.18	Hue + Brightness
1.19	Saturation + Brightness
1.20	Hue + Saturation + Brightness
2.1	Baseline (Deformed + Color)
2.2	Rotation + Hue
2.3	Scaling + Hue
2.4	Rotation + Saturation
2.5	Scaling + Saturation
2.6	Rotation + Brightness
2.7	Scaling + Brightness
2.8	Rotation + Scaling + Hue
2.9	Rotation + Scaling + Saturation
2.10	Rotation + Scaling + Brightness
2.11	Rotation + Scaling + Hue + Saturation + Brightness
3.1	Baseline (Original + Deformed)
3.2	Color Jittering (A)
3.3	Scaling (B)
3.4	Rotation (C)
3.5	A + B
3.6	A + C
3.7	B + C
3.8	A + B + C

Table 7. Hyperparameter Model

Hyperparameter	Value
Epoch	100
Learning Rate	0.01
Batch Size	16

7) Analysis And Drawing Conclusion

At this step, information will be obtained that can be used for answering the purpose of the research, in the form of conclusions from the experimental results that have been carried out in this research. From the experimental results that obtained, it is known how much affect the application of data augmentation has on the model YOLOV8 in detecting types of beverage packaging waste.

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4. RESULTS AND DISCUSSION
4.1. Result

The results obtained from the entire set of experimental scenarios that have been performed. Based on the AP value per class in each experimental scenario method performed, the can class with the implementation of the scaling transformation augmentation method and combining with original data has the highest AP value which is 0.913.

Then, for the mAP accuracy value of the results, the method that has the highest mAP value is in the experimental scenario with the implementation of the scaling and rotation transformation augmentation method and combining with the original data, which is 0.884.

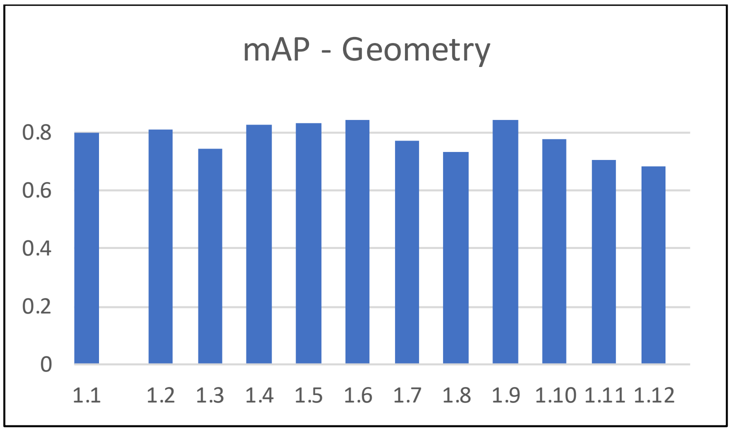

Figure 17. Mean Average Precision Geometry

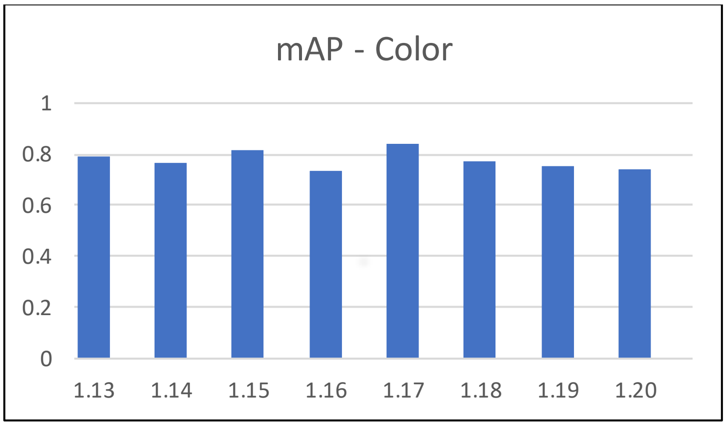

Figure 18. Mean Average Precision Color

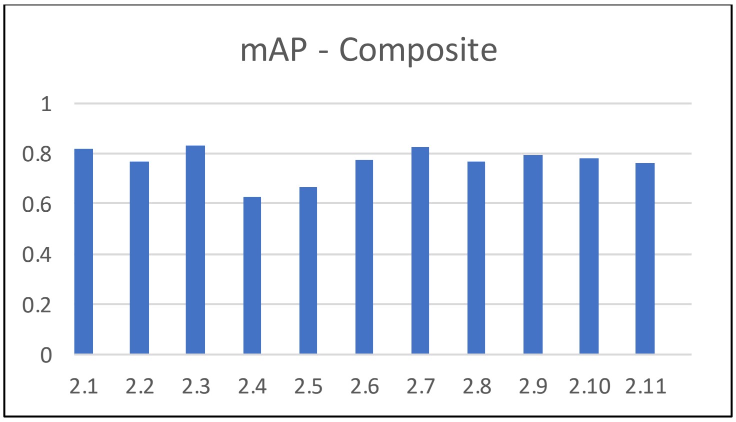

Figure 19. Mean Average Precision Composite

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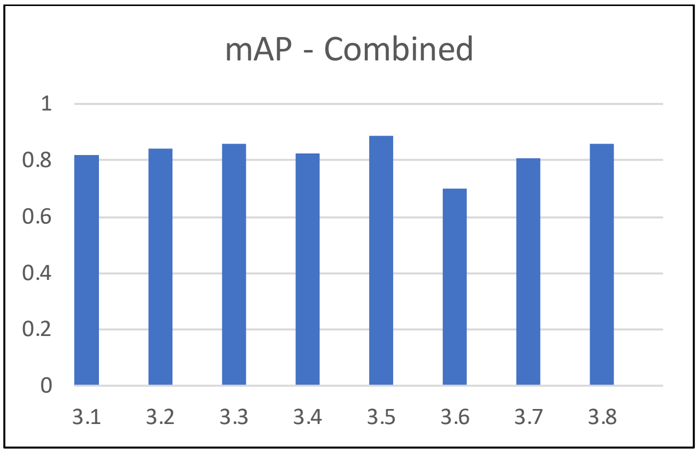

Figure 20. Mean Average Precision Combined

Also, experiments for testing the model with detection results were performed on each scenario. Based on the percentage of object detection results that are detected correctly by the model, the highest results occur in the scenario that implements a combination of scaling and rotation transformations method where the percentage is 100%, which case increased by 6.67% from the baseline.

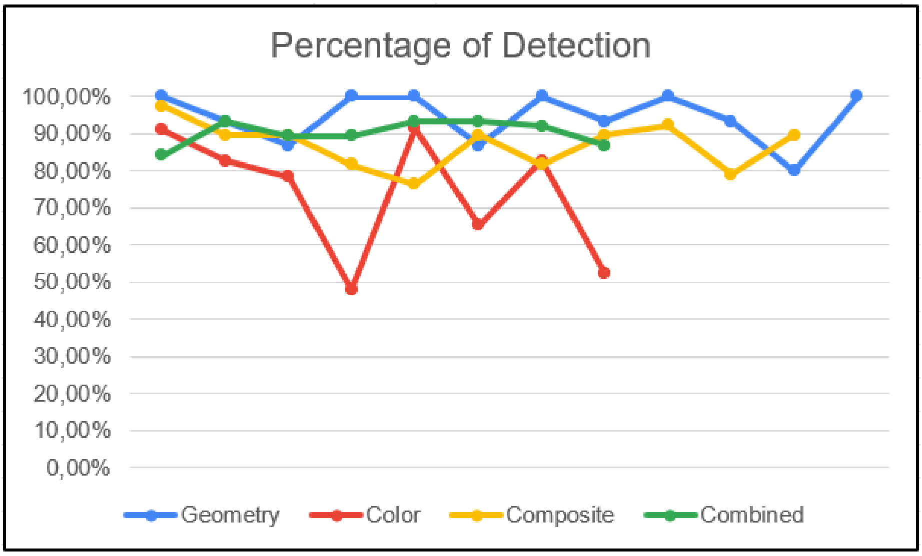

Figure 21. Percentage of Detection

4.2 Discussion

There were four experimental scenarios that had an improved mAP value (accuracy) as well as the number of detections, compared to the baseline (without augmentation). In the geometry transformation, four methods increased the mAP value, while none increased the number of detections. Second, two methods increased the mAP value for the color transformation, but only one method increased the number of detections. For the composite transformation, four methods increased the mAP value, but none increased the number of detections. The mAP value of four, the combined transformation, and five methods increased, and the number of detections increased for all methods.

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5. CONCLUSION

As a result of several experimental scenarios, data enhancement using geometry and color transformations conducted in this research can improve the mAP value's accuracy and reduce detection errors in the model. These results demonstrate that data augmentation can influence the model. Expanding the research object to include cardboard beverage packaging waste object classes, plastic cup beverage packaging waste, and others is possible. Additionally, when employing geometry and color transformation data augmentation, additional methods can be explored and analyzed on the data to be utilized. For instance, the shear, translation, and RGB, CIELAB methods of geometry transformation.

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