Real-Time Detection of Floating Debris in Waterways Using YOLOv8

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Waterways have played a large role in our daily activities such as electricity, food, transport, and agriculture. However, the constant urbanization of most waterways has led to a significant amount of pollution in the multiple bodies of water, with mostly floating debris contributing to this environmental threat. The Philippines has contributed to immense discharge of plastic waste into rivers. Furthermore, the prevalence of invasive aquatic plants disrupt the ecosystem of the water bodies and affect economic activities. Traditional methods of monitoring water surface debris are inefficient and resource-demanding. This study proposes the development of an object detection model based on YOLOv8 to identify floating debris on a water surface accurately and in real-time, including garbage and invasive plants. The researchers created a dataset of floating debris. Image preprocessing techniques such as resizing, orientation, resizing, contrast adjustment, and augmentation were done to improve the dataset. The researchers tuned the model in terms of optimizer using Adam and SDG, and learning rates of 0.01 and 0.001. Upon evaluation, the researchers determined that the model using the SGD optimizer performed better than the model using Adam optimizer in floating debris detection. The researchers further determined that the model performed best when utilizing the best weights from training and a learning rate of 0.001 with the SGD optimizer.

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: Water surface debris, object detection, YOLOv8, floating debris detection, environmental monitoring

ACM Reference Format:

Jan Edgar E. Tupas, Miguel T. Soniel, Christian Henry Miguel E. Caruz, and Darryl B. Babar. 2024. Real-Time Detection of Floating Debris in Waterways Using YOLOv8.

1 INTRODUCTION

Waterways are essential in the movement of water for purposes such as navigation, irrigation, and drainage. They are necessary for human endeavors like industry, agriculture, and transportation. The capacity to recognize and locate small items on the water's surface can enhance the capacity to carry out environmental surveillance, uphold civil infrastructure, safeguard civil water supplies from pollution, or guide utility and security personnel and vessels [20]. Rapid urbanization has brought about immense pollution in waterways. The amount of floating debris, which includes dead plants and animals as well as human-discarded household trash, has drawn increasing attention [22]. Floating items on the water's surface of rivers, like bags, plastic bottles, and aquatic plants, typically degrade slowly or never at all. If these floating items are left in the water for an extended period of time, they will pollute the environment [21]. Furthermore, the accumulation of water surface debris over time can impede the normal flow of water in rivers, streams, canals, and other waterways. Waterways in the Philippines are constantly bombarded with water surface debris such as garbage and invasive plants. The Philippines, with 466 out of 1,656 rivers worldwide, was responsible for discharging over 356,371 metric tons of plastic waste every year [19]. The 27-kilometer Among the top 50 rivers that discharge the most debris and plastic into the ocean are the Pasig, Pampanga, Agusan, Libmanan, Zapote, and Iloilo rivers located in the Philippines. Due to the lack of resources and research in the Philippines, there is not much information available regarding the monitoring of plastic wastes [18]. Apart from garbage, invasive plants also negatively impact waterways. The most harmful alteration in freshwater ecosystems is biological invasion, which results in substantial harm and affects the ecosystem's structural organization and functional integrity [16]. Invasive alien plants have a capacity to lower mean annual runoff and river flows by increasing transpiration and evaporation losses [17]. By forming dense surface canopies that shade out lower-growing native plants and obstruct water flow, boat traffic, and fishing, invasive plants prevent native plant growth and hinder human uses of waters. Additionally, fish habitat quality is drastically altered by dense surface canopies [15].

Monitoring water surface debris can aid in early detection of pollution, environmental assessment, and detection of debris accumulation. With the advancement of deep learning and computer vision, object detection has become a reliable tool to automate various human tasks. The application of object detection includes optical character recognition, self-driving cars, face detection and recognition, pedestrian detection, medical imaging, ball tracking in sports, and iris recognition for identity verification [13]. Object detection is divided into two-stage target detection, such as Region-based Convolutional Neural Network (R-CNN), Spatial Pyramid Pooling (SPP-Net), Fast R-CNN, Faster R-CNN, and one stage target detection, such as You Only Look Once (YOLO) and Single Shot Detector (SSD) [14]. One stage detection algorithms prioritize speed at the expense of accuracy by using global regression and classification to generate the location and category of the target object [12]. Thus, these algorithms are best implemented for real-time scenarios.

The YOLO target detection algorithm can produce direct neural network outputs of bounding box positions and categories due to its small size, quick computation, and simple structure [11]. In autonomous driving, YOLOv4 outperforms, SSD and RetinaNet in detection accuracy [10]. YOLOv4 also surpasses the accuracy of Region-based Fully Convolutional Neural Network (R-FCN), Mask R-CNN, SSD, and RetinaNet in road object detection [9]. Comparative studies evaluated the performance of YOLO variants and found that the base YOLO variants outperform their predecessors in object detection tasks [8][7][6]. The latest variant of the YOLO algorithms is YOLOv8 and is a state-of-the-art computer vision model. YOLOv8 processes objectness, classification, and regression tasks independently using an anchor-free model with a decoupled head which enhances accuracy [5]. YOLOv8 has been applied in many tasks such as road defect detection [4], UAV object detection [3], pedestrian tracking [2], underwater object detection [1], and provide effective and improved results. There is a lack of research that focuses on using YOLOv8 for water surface object detection. With the improvements of YOLOv8 from its predecessors and effective and promising results from recent object detection works, the YOLOv8 variant is used and explored in the study.

In this paper, the researchers developed an object detection model for the detection of floating debris on a water surface. The floating debris detected by the researchers were garbage, invasive aquatic plants, branches, and leaves. The researchers leveraged the YOLOv8 detection algorithm since recent object detection works using YOLOv8 yielded promising and effective results and research on using the algorithm with floating object detection is limited.

The primary objective of the study is to develop a YOLOv8 model with the purpose of accurately identifying and localizing instances of water surface debris within waterways, contributing to the development of effective and efficient methods for water surface debris monitoring. The specific objectives of the study are the following: (1) To develop a YOLOv8 model that effectively and accurately detects water surface debris using the created dataset; (2) To evaluate and compare the performance of the YOLOv8 model with varying optimizers and learning rates; (3) To assess the detection performance of the YOLOv8 model for each class.

2 RELATED WORKS

This section provides an overview of related research studies and literature conducted by researchers regarding floating debris detection on the water surface through machine learning. The selected and reviewed literature are discussed.

2.1 Negative Impacts of Floating Debris on Waters

Any trash or vegetation near the water's surface that obstructs the ecosystem, the area's navigability, or recreational activities is considered floating debris. Debris like floating trash, plastics, invasive aquatic plants, sticks, logs, and other marine litter can be either naturally occurring or man-made. Meijer et al. [19] conducted a study in 2021 to determine global riverine plastic emission distribution into the ocean. The authors found that a significant portion of global emissions are caused by small and medium-sized rivers and 98.5% of plastic waste stays trapped in terrestrial settings, where it builds up and gradually contaminates aquatic ecosystems. According to a report by Tekman et al. [28], 88% of 297 marine species were adversely affected by plastic debris. The authors identified the main negative impacts of plastic debris to marine life as entanglement, ingestion, smothering, and chemical pollution, resulting in the injury or death of marine life. In the work of Allsopp et al. [27], 80% of marine debris originate from land-based sources, categorized into tourism litter, sewage-related debris, fishing related debris, and ship wastes. The authors also note on the potential invasion of alien species through floating plastic debris that signifies a potential threat in marine environment. Apart from garbage, invasive aquatic plants also have ecological and economic impacts. According to Madsen [15], invasive aquatic plants Diminish water quality, diminish biodiversity, inhibit the growth of native plants, elevate the risk of extinction for vulnerable species, and alter the overall quality of the habitat. The author further states that in terms of economic impacts, invasive aquatic plants Disrupt commercial navigation, heighten the occurrence of floods, compromise drinking water quality, and provide a breeding ground for disease-carrying insects. Human resources are primarily used in the monitoring and management of water-floating trash, and frequent, purposeful salvage and cleaning of floating trash requires significant amounts of both human and material resources but is inefficient [29]. Future developments will favor mechanized salvage methods, with research into floating garbage detection algorithms on the water's surface driving this trend [26].

2.2 YOLO-based Floating Debris Detection

There is not shortage in studies regarding object detection and its application to various tasks. Various object detection algorithms have been developed, implemented, and evaluated in diverse settings such as in vehicles, medical imaging, and sports tracking [13]. Object detection algorithms are either one-stage or two-stage where two-stage prioritizes accuracy and one-stage focuses on speed [12]. In applying object detection for real-time tasks, one-stage object detection algorithms are utilized. The YOLO algorithm uses end-to-end network structure to achieve real-time requirements with fast detection speed [7]. Numerous studies have focused on utilizing the YOLO series for detecting floating objects on a water surface. Recent studies are reviewed to aid in the development of a YOLOv8 model for floating debris detection. In the study of Jiang et al. [29], an improved YOLOv7 with ACanny PConv-ELAN and multi-scale gated attention for adaptive weight allocation (MGA) was proposed to detect floating garbage. The Yellow River (YRDG) water-floating garbage dataset was created and used by the authors. The YOLOv7 network's incorporation of ACanny and PConv-ELAN enabled precise feature extraction from water-floating trash. In order to reduce the likelihood of a missed detection, the authors also implemented an MGA attention. The proposed APM-YOLOv7 model outperformed the benchmark YOLOv7, increasing the mean average precision (mAP) by 7.02% and recall by 11.82%, according to the authors' conclusion. The authors advise on expanding and diversifying the dataset since it limits the performance of the model with inconsistent detection performance for distinct categories. The study of Lin et al. [30] proposed in their study the FMA-YOLOv5 algorithm for detecting floating debris in a waterway. The authors integrated a feature map attention (FMA) layer to improve feature extraction, and FPN and PENet to improve the fusion of features. The authors collected 2400 floating debris images with 8 categories and applied mosaic augmentation to increase the training dataset to 4800. The authors note on the improvement of mAP due to the augmentation. The authors concluded that the proposed model outperforms the YOLOv5s with an increase in mAP by 2.18%. The authors note that the model can be used to monitor floating objects but improvements are needed in the detection of blurred and dense objects. In the study of Zailan et al. [25], the authors utilized YOLOv4 to detect floating debris for a riverine monitoring system. The authors collected and augmented 300 images resulting in 900 images for training. The authors used the classes styrofoam, plastic bags, plastic bottles, aluminum can, and plastic container, and 30 images per class was used for testing. The authors used transfer learning on MS-COCO dataset to obtain pre-trained weights for training. The authors incorporated a spatial pyramid pooling (SPP) block to improve the operation speed of the YOLOv4 model. The authors compared the performance of the model with and without transfer learning and concluded that using transfer learning decreases the training time and improves model performance in terms of mAP, F1 score, Average IoU, Precision, and Recall. The authors also note that an IoU threshold of 0.3 results in the best performance of the model for classifying all classes. The authors suggest creating a more challenging dataset in the future and further optimizing the proposed YOLOv4 model to reduce detection time and retain high classification performance. In a study by Xu et al. [31], a YOLOW algorithm is developed and proposed to automatically detect water objects. The authors used the publicly available FLOW-Img dataset with 2000 images and 5271 annotated objects. The authors improved the YOLOv5 algorithm by incorporating a SPDCS module, a SPPAUG model, and a C2f module. The authors stated that the SPDCS module improves the preservation of key information in the channel dimension by increasing the convolutional operations and attention mechanisms. The authors also discuss that the SPPAUG module improves object detection performance while maintaining swift and effective detection. Furthermore, the authors stated that the C2f module incorporates a feature fusion operation to improve feature representation capacity by combining feature maps from various levels and scales. With a learning rate of 0.1%, epoch of 300, and batch size of 20, the authors concluded that the proposed YOLOW algorithm outperforms the YOLOv5 variants in terms of Precision, Recall, and mAP by 6.4%, 2.3%, and 4.3% respectively. The authors noted that the YOLOW model is larger compared to the original YOLOv5 model and future work can focus on developing a lightweight model based on YOLOW. To address the issues of traditional image processing techniques for floating debris detection, Qiao et al [22] proposed in improved YOLOv5 model in their study. The authors developed and used the SWFD dataset consisting of floating debris images including plastic bottles, plastic bags, foam, branches, and floating algae. The authors improved the YOLOv5 model by introducing the coordinate attention module, improving the extraction of features from small and dense floating debris. The authors also introduced a bidirectional feature pyramid network to that adopts efficient bidirectional cross-scale connection and weighted feature fusion to improve feature extraction and object detection accuracy especially for small floating debris. The authors compared the performance of the proposed model to state-of-the-art models encompassing Faster R-CNN, SSD, YOLOv3, and YOLOv5s. The authors concluded that the proposed model obtained performance scores of 96.5%, 95.8% in Recall, Average Precision (AP) respectively and outperformed the state-of-the-art. The authors noted on the lightweight capability of the model, allowing it to be integrated with mobile devices for floating debris detection.

2.3 Comparing YOLOv8 with YOLO Variants

According to Terven et al. [5], YOLOv8 processes objectness, classification, and regression tasks separately using an anchor-free model with a decoupled head. By allowing each branch to concentrate on its specific task, this design enhances the overall accuracy of the model. In the work of Maity et al. [24], the authors compared the performance of recent YOLO variants, namely YOLOv5, YOLOv7, and YOLOv8 for vehicle detection. The authors used two AVD datasets for the experiment, namely the JUVDsi v1 and IRUVD. The authors evaluated the performance of the models in terms of Precision, Recall, and mAP. All three models were run for 25 epochs. With the JUVDsi v1 dataset, the YOLOv8 outperformed the YOLOv5 and YOLOv7 by a small margin but all three models performed well with a mAP50 score of 0.755, 0.816, and 8.817 for YOLOv5, YOLOv7, and YOLOv8 respectively. In the IRUVD dataset, all models were very effective but the YOLOv7 model performed the best with a mAP50 score of 0.960 compared with that of YOLOv5 with 0.893 and YOLOv8 with 0.946. Meanwhile, the study of Adegun et al [23] comprehensively evaluated the performance of deep learning-based object detection algorithms for detecting objects in remote sensing statellite images. The authors compared the model performance of Detectron2, YOLOv5, YOLOv6, YOLOv7, and YOLOv8. The authors created their dataset of 92 satellite images from Google Earth Engine with 5 classes namely residence, roads, shoreline, swimming pool, and vegetation. Data augmentation was done to increase the dataset. The authors evaluated the performance of the models with their dataset. The results showed that the YOLOv8 model outperformed the other object detection models. The YOLOv8, YOLOv7, YOLOv6, YOLOv5, and Detectron2 models obtained a Precision score of 68%, 54.5%, 53.2%, 53.4%, and 50% respectively, a Recall score of 60%, 46.2%, 47.4%, 49.7%, AND 32.7% respectively, a mAP50 score of 43%, 34.1%, 32.1%, 27%, and 16% respectively, and a speed of 0.2ms, 0.3ms, 0.4ms, 0.5ms, and 0.9ms respectively. The authors concluded that the YOLOv8 model had superior performance over other models with the created dataset, as well as the Pascal VOC and Visdrone datasets. YOLOv8 has proven to be effective and produce better results when applied to various tasks, including underwater object detection [1], pedestrian tracking [2], road defect detection [4], and UAV object detection [3]. YOLOv5 and YOLOv7 were commonly used in the reviewed studies relating to floating object detection and YOLOv8 is yet to be utilized. This provides an opportunity for exploring and implementing YOLOv8 for floating debris detection.

3 METHODOLOGY

This section provides an overview of the materials and methods used in the study. The researchers collected and curated their own dataset of floating water debris. Image preprocessing techniques were applied to the dataset. The processed data were fed into an object detection model for training and testing. The researchers optimized the model to obtain the best performance. The methodology encompasses the following: data collection, data preprocessing, model training and validation, model testing, and model performance evaluation. The conceptual framework of the study is illustrated in Figure 1.

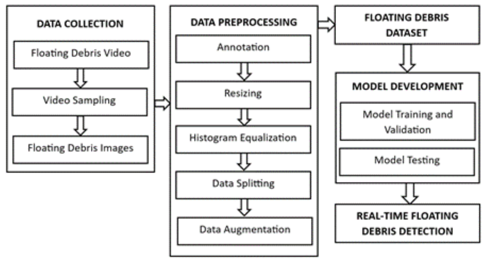

Figure 1: Conceptual Framework of the Study

3.1 Data Collection

The researchers curated and created their own dataset for the study. The video of floating debris on the water surface of the Pasig River was taken in Globe Circuit Event Grounds in the Philippines. The 24.1 megapixel CMOS Canon M50 Mk II camera was used to capture the video in 1080p Full HD resolution. To ensure that the floating objects can be clearly seen, the video was taken during daytime. The camera was positioned with a height of around 162 cm from the ground, a distance of around 10 feet from the water, and at an angle of around 45 degrees all throughout the 19-minute session. The result was a 19-minute video that captured floating debris on the water surface of Pasig River in a consistent manner.

3.2 Dataset

The researchers utilized the 19-minute video to create their own dataset. Upon reviewing the video, the prominent objects identified were garbage, aquatic plants, branches, and leaves. Hence, these were the classes used in the study. Roboflow was used to sample the video by 1 frame per second. This resulted in a total of 1144 images. The instances of each object class in each image were manually counted and totaled and is shown in Table 1. A balanced dataset where the distribution of classes is equal is preferred to avoid biased model training and overfitting. In this case, the dataset has a significant imbalance where branches and invasive aquatic plants were a minority class. To alleviate the impact of this issue, augmentation was performed resulting in a total of 2746 images.

Table 1: Total Instances of Each Class

Debris Type	Total Instance
Garbage	7284
Leaves	2830
Branches	169
Aquatic Plants	149
Total	10432

3.3 Data Preprocessing

The quality of the data impacts the performance of the object detection model. Data preprocessing ensures suitable data for model training, enhancing the model's generalization and feature extraction capabilities. The researchers used Roboflow in implementing the data preprocessing methods. The researches first annotated the images based on the classes of garbage, leaves, branches, and invasive aquatic plants. The images were auto-oriented. The images were resized to 640 x 640 to ensure better optimization and compatibility with the model. Auto-adjusting contrast through histogram equalization was performed on the images to improve the visibility of details and features in the images, especially since the objects are small in size and the environment may influence model performance. The data was split into into training, validation, and testing with a ratio of 70:20:10. Data augmentation is performed on the training dataset to artificially increase its size. This helps in addressing the dataset imbalance, model generalization, robustness, and reduces overfitting. The augmentation techniques performed are shown in table 2. 3 outputs per training example were produced after augmentation. As a result, the dataset consisted of 2403 images for the train set, 229 images for the valid set, and 114 images for the test set for a total of 2746 images.

Table 2: Data Augmentation Techniques

Augmentation Technique	Type
Flip	horizontal, vertical
90° Rotation	clockwise, counter-clockwise, upside down
Rotation	-15° to +15°
Shear	+-10° horizontal, +-10° vertical
Saturation	-25% to +25%
Brightness	-15% to +15%
Exposure	-10% to +10%
Noise	up to 0.1% pixels

3.4 Model Training and Validation

Google colab with a T4 GPU was used to develop the object detection model. The YOLOv8 object detection algorithm was used in this study for floating debris detection. With the limited dataset, the researchers opted for a YOLOv8 model pre-trained with the COCO dataset as opposed to training from scratch. The model was custom trained with the created dataset using the pre-trained weights with an epoch of 300 and batch size of 16. During model training and validation, TensorBoard provides logging information in a form of a multi-curve graph that shows training and validation loss. Thus, the researchers used TensorBoard to note on the performance of the model at various stages. The researches also used patience. In YOLOv8, patience allows for the early stopping of training when there are no more improvements made. Patience was set to 50, meaning that training was stopped when no improvements were made for the last 50 epochs. After the initial testing and validation, the researchers performed hyperparameter tuning, focusing on optimizer and learning rate. The process was iterated to determine if the performance of the model could be improved.

3.5 Model Testing

The model was tested after validation and tuning. Here, the model is evaluated on data that it has not yet seen during the training process to assess how well it generalizes to new data and estimate its performance in real-world data. The researchers evaluated the testing performance of the model through widely utilized metrics, namely mean average precision at an IoU threshold of 0.5 (mAP50), and ranging from 0.5 to 0.95 (mAP50-95), precision (P), recall (R), f1 score, and confusion matrix.

4 RESULTS AND DISCUSSION

This section presents the results produced by the YOLOv8 model in detecting floating debris. The effects of varying optimizers and learning rates on model performance is evaluated. The performance of the model in detecting objects per class is also discussed.

4.1 Impact of Optimizers and Learning Rates

The researchers compared the impact of two optimizers and learning rates to the object detection performance of the YOLOv8. The optimizers evaluated were the Adam Optimizer and Stochastic Gradient Descent (SGD). The learning rates assessed were 0.01 and 0.001. Upon completing model training, YOLOv8 provides the best weights for the model, as well as the weights used in the last epoch during model training. In this case, the best and last weights were also compared. The model was pre-trained with the COCO dataset. The weights were used to train the model with the dataset of floating debris created by the researchers. The model was trained using 300 epochs, batch size of 16, and patience of 50. These parameters were kept constant to focus on the influence of the optimizers and learning rates. Table 3 shows the validation results of the model based on the optimizer, learning rate, and the weights attained from training.

Table 3: Performance of the YOLOv8 Model with Varying Optimizers, Weights, and Learning Rates

Optimizer	Weights	Learning Rate	mAP50	mAP50-95	Precision	Recall	F1 Score
Validation							
Adam	Best	0.01	0.836	0.405	0.840	0.772	0.805
Adam	Best	0.001	0.861	0.453	0.877	0.816	0.845
SGD	Best	0.01	0.860	0.473	0.841	0.831	0.836
SGD	Best	0.001	0.864	0.470	0.854	0.828	0.841
Testing							
Adam	Best	0.01	0.819	0.419	0.819	0.746	0.781
Adam	Best	0.001	0.854	0.454	0.847	0.797	0.821
Adam	Last	0.01	0.005	0.001	0.002	0.094	0.004
Adam	Last	0.001	0.869	0.453	0.888	0.844	0.865
SGD	Best	0.01	0.850	0.470	0.888	0.826	0.856
SGD	Best	0.001	0.872	0.467	0.882	0.855	0.868
SGD	Last	0.01	0.851	0.467	0.879	0.832	0.855
SGD	Last	0.001	0.859	0.462	0.892	0.812	0.850

In the validation, the performance of the model when using the Adam optimizer improves in all metrics when learning rate is reduced to 0.001. Meanwhile the performance of the model using the SGD optimizer varies according to the metrics when learning rate is reduced. In this case, although the Map50, precision, and the f1 score of the model is improved, the map50-95 and recall of the model is reduced. In testing, the SGD optimizer obtained better performance scores than the Adam optimizer based on the evaluation metrics. The model SGD optimizer with a learning rate of 0.001 and with the best weights obtained from the training obtained the highest scores in mAP50 with 0.872 or 87.2%, recall with 0.855 or 85.5%, and f1 score with 0.868 or 86.8%. But it achieved higher scores in precision using the last epoch weights from training at 0.888 or 88.8%, while it achieved a higher Map50-95 score with the best weights and a learning rate of 0.01 at 0.470 or 47%. Meanwhile the model using Adam optimizer had best performance with a learning rate of 0.001 and the last epoch weights from training with a mAP50 score of 0.869 or 86.9%, precision score of 0.888 or 88.8%, recall score of 0.844 or 84.4%, and f1 score of 0.865 or 86.5%. The model using Adam optimizer with a learning rate of 0.01 and last epoch weights performed the poorest but may be attributed to a longer calculation than the provided NMS time limit. It can be observed that decreasing the learning rate improves the model, in terms of the mAP50, mAP50-95, precision, and recall when using the Adam optimizer, whereas improvements in the SGD optimizer are observed in map50, and recall and f1 scores when using the best weights from training. It can also be observed that the model using SGD outperforms the model using Adam optimizer in almost all cases when both optimizers use the same parameters. It is important to note that the model was run with 300 epochs but performed early stopping when no improvements from the latest 50 epochs are identified. As such, the model training stopped at 170 epochs when using the SGD optimizer 0.01 learning rate and best results were observed at epoch 120. With SGD and a learning rate of 0.001, training stopped at 123 epochs where best results were observed in epoch 73. With Adam and a learning rate of 0.01, training completed with 151 epochs and best results were observed at epoch 101. Lastly, with Adam and a learning rate of 0.001, training was stopped after 152 epochs where the best results were obtained in epoch 102.

4.2 Evaluating the Object Detection per Class

Table 4: Model Performance in Detecting Each Class

Class	Best Adam (lr=0.01)					Best SGD (lr=0.01)				
	mAP50	mAP50-95	Precision	Recall	F1 Score	mAP50	mAP50-95	Precision	Recall	F1 Score
Aquatic Plant	0.995	0.634	0.762	1	0.865	0.995	0.749	1	0.95	0.974
Branch	0.936	0.489	0.929	0.812	0.867	0.959	0.534	0.910	1	0.953
Garbage	0.568	0.222	0.791	0.445	0.570	0.639	0.246	0.806	0.558	0.659
Leaf	0.778	0.331	0.796	0.726	0.759	0.807	0.349	0.834	0.797	0.815
Class	Best Adam (lr=0.001)					Best SGD (lr=0.001)				
	mAP50	mAP50-95	Precision	Recall	F1 Score	mAP50	mAP50-95	Precision	Recall	F1 Score
Aquatic Plant	0.995	0.680	0.938	1	0.968	0.995	0.667	1	0.994	0.997
Branch	0.939	0.553	0.830	0.875	0.852	0.991	0.605	0.941	1	0.970
Garbage	0.633	0.236	0.786	0.507	0.616	0.660	0.252	0.760	0.594	0.667
Leaf	0.848	0.348	0.833	0.805	0.819	0.841	0.342	0.828	0.832	0.830
Class	Last Adam (lr=0.001)					Last SGD (lr=0.001)				
	mAP50	mAP50-95	Precision	Recall	F1 Score	mAP50	mAP50-95	Precision	Recall	F1 Score
Aquatic Plant	0.995	0.674	0.992	1	0.996	0.995	0.659	1	0.958	0.979
Branch	0.980	0.556	0.941	0.990	0.965	0.984	0.605	0.912	1	0.954
Garbage	0.635	0.235	0.758	0.561	0.645	0.642	0.238	0.811	0.534	0.644
Leaf	0.865	0.347	0.862	0.825	0.843	0.814	0.347	0.846	0.756	0.798

Table 4 shows the performance of the model in detecting each class based on the specific optimizer and learning rate. It can be observed that the model can effectively detect aquatic plants with both optimizers and with varying learning rates. This can be attributed to the size of the aquatic plants, which aids the model in terms of visibility. The model achieves a constant 0.995 or 99.5% mp50. The model using SGD outperforms the model using Adam in terms of precision, obtaining a constant 1 or 100%. Meanwhile the model using Adam optimizer outperforms the model using SGD in terms of recall, also obtaining a constant 1 or 100%. The model can also effectively detect branches as show in the high metric scores. The model using the SGD optimizer with a learning rate of 0.001 and with the best weights from training perform the best in distinguishing branches as shown in the obtained metric scores with an map50, map50-95, precision, recall, and f1 score of 0.991 or 99.1%, 0.60 or 60.5%, 0.941 or 94.1%, 1 or 100%, and 0.970 or 97% respectively. The model struggles to detect garbage, despite the class having the most number of instances in the dataset. Garbage detection peaked its highest at only 0.660 or 66.6% map50 with the model using SGD optimizer with the best weights and learning a rate of 0.001. The model was able to detect leaves better than garbage as shown. The Adam optimizer with the last epoch weights and a learning rate of 0.001 obtained the highest map50 for detecting leaves at 0.865 or 86.5%. In reviewing the images, the annotated garbage instances were small and blended with the water which may have limited the model's capacity to detect the garbage instances effectively. Furthermore, a 25% confidence rate was implemented to avoid detection of unlikely images. Because of this, tiny garbage instances, as well as other small objects, did not reach the specified confidence interval to be detected.

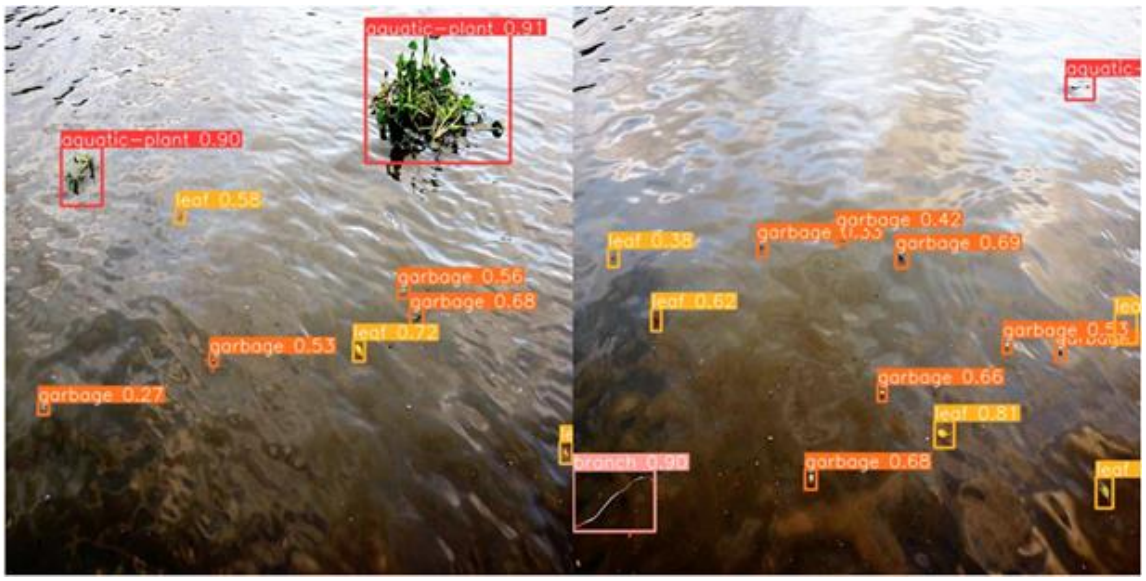

Figure 2: Floating Debris Detection of YOLOv8 model using SGD Optimizer

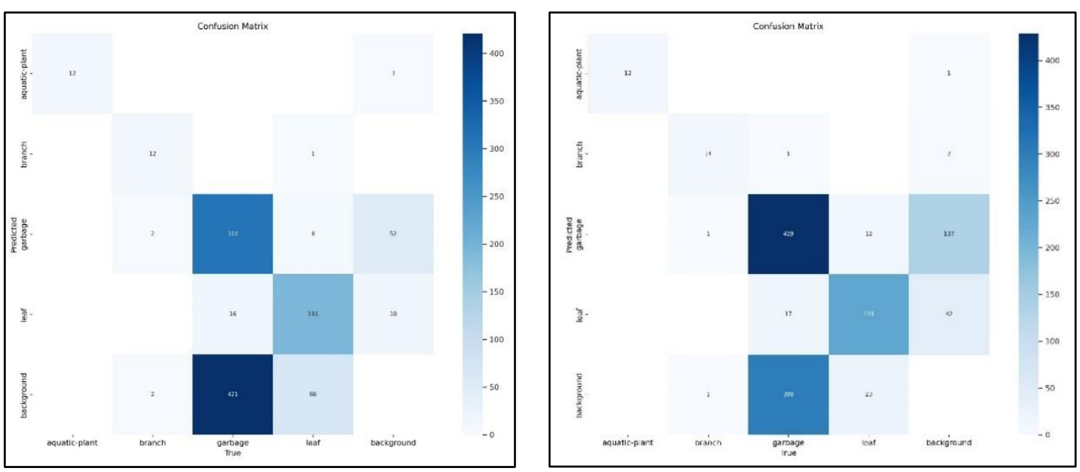

Figure 3: Confusion Matrices of YOLOv8 Model using Adam with 0.01 and 0.001 Learning Rates

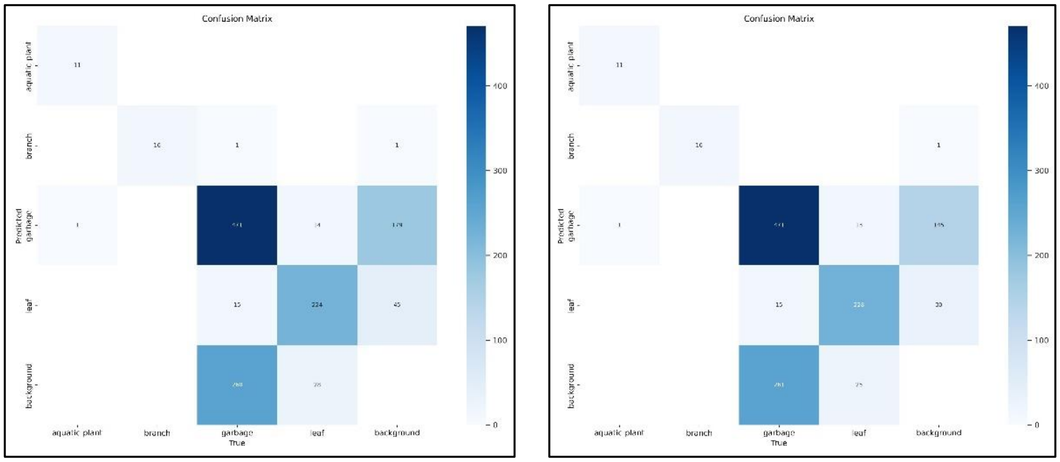

Figure 4: Confusion Matrices of YOLOv8 Model using SGD with 0.01 and 0.001 Learning Rates

Figures 3 and 4 present the confusion matrices of the model using Adam and SGD with 0.01 and 0.001 learning rates. In figure 3, the model accurately detected and classified all instances of aquatic plants. Branches were also identified but some were misclassified as garbage. Similarly, leaves were properly detected but some were misclassified as garbage and branch. The model struggles to detect garbage. Although numerous instances were correctly classified, the model misclassifies the other as background, attributed by the tiny instances of the garbage and the influence of the water where the debris floats. In figure 4, the model using SGD show better performance. Branches were effectively identified by the model but an instance of the aquatic plant was misclassified, and instances of leaves were misclassified as garbage or background. This can be attributed to the small size and color of leaves which may closely resemble instances of garbage. Garbage was also misclassified by the model but in lesser instances in comparison to the model using Adam. The model struggles to differentiate garbage instances with the water which can be attributed to the similarities in color as the water surface of the Pasig River is slightly dark and while garbage like plastics is transparent. Furthermore, the waves in the river submerges instances of garbage reducing vision. This leads to the misclassification of garbage. Overall, the model using SGD optimizer performs better in the object detection task against the Adam optimizer, especially with a learning rate of 0.001 and using the best weights from training.

5 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The researchers utilized YOLOv8 to develop a model for floating debris detection on waterways. The researchers created their own floating debris dataset and utilized it to train the object detection model. To improve the dataset, the researcher performed preprocessing and augmentation techniques, improving the quality of the data and increasing the size of the dataset. The researchers acknowledge the limitation of the created dataset due to the imbalance between classes. The researchers successfully compared the performance of the model with varying optimizers and learning rates using SGD and Adam optimizers, 0.01 and 0.001 learning rates, and best and last weights generated after model training. The researches also successfully assessed the performance of the model for each surface debris class. The researchers that the model using the SGD optimizer performs better overall than the model using the Adam optimizer. The researchers determined that the model using the SGD optimizer produced lesser errors in detecting and classifying the floating debris objects. Furthermore, the researchers used the model using the SGD optimizer, best weights, a learning rate of 0.001, to effectively detect floating debris on waterways. The researchers determined that the model's capacity to accurately detect floating debris is influenced by the size and color of the object. Tiny objects and those resembling water exhibit low confidence, failing to meet the necessary minimum confidence threshold of 25%.

5.2 Recommendation

The researchers noted on the limitations of the created dataset, especially due to its significant imbalance. The dataset also consisted of only four classes. To develop and improve object detection models for floating debris detection, the researchers recommend creating a dataset of floating debris by collecting new data and integrating more classes. It is recommended that the classes must be balanced and represented by sufficient images as this will aid in model development. The researchers also recommend exploring more image preprocessing techniques to improve the quality of the dataset. Advancements in deep learning could be applied in this case. In the study, the optimizer and learning rate were the only parameters used to tune the model. It is also recommended to fine-tune the object detection model with more hyperparameters such as batch size, anchors, epochs, momentum, and weight decay to improve model performance. The model can also be incorporated in applications to effectively implement real-time detection of floating debris on waterways, especially in areas where floating debris is prevalent, serving as a simple solution to a large problem.

ACKNOWLEDGMENTS

The researchers would like to express their gratitude to their advisor Prof. John Paul Tomas for support in this study. His guidance was necessary for this study. The researchers would also like to thank those who contributed for the completion of this research study.

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