https://doi.org/10.32010/mpmc2024.057

THE LOCALIZATION OF OIL LEAKS IN THE SEA USING SATELLITE AND DRONE IMAGES WITH ARTIFICIAL INTELLIGENCE MODELS

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ABSTRACT
Computer Vision, Deep Learning, and Machine Learning Algorithms make it possible to detect various dynamic issues in nature. Tankers, oil fields, oil pipelines, and hydrocarbon leaks and spills create serious problems for the sea ecosystems. [1] Utilizing this type of model can help detect oil leaks promptly, guide scientists' predictions, compile cleaning plans, make urgent decisions on time, and stop or reduce the negative impacts of those incidents. Numerous recent scientific studies have been taken on this issue [2-7]. Illegal Pollution requires continuous monitoring and remote tracking technique employing satellites is an intriguing solution for the detection of oil leaks [8]. In this article, the solution to this problem is provided with the help of a recently updated model [9]. Specifically, emphasize the automatic approach of differentiation of oil marks and other similar marks.
Keywords: Oil, Oil Leak, Artificial Intelligence, Image Localization Models, PyTorch, YOLOv8.

Introduction

One of the most serious ecological issues that can quickly cause damage to a large area is oil spills. A multitude of factors, such as pipeline rust and disregard for process safety rules, can lead to oil leaks. One thing is for sure: preventing the environmental catastrophe may depend greatly on early problem diagnosis [10]. Deep learning models can assist us in detecting oil spills from faraway locations, which makes early detection tools crucial. About the image samples (Fig. 1.):

The image samples are sourced from the Roboflow online platform, an online open-source model dataset, which has the general use license, titled "OilSpill Dataset". The dataset consists of 2500 images and was created in 2023. The images, captured by drones and satellites, have dimensions of 640x640 pixels. The images are collected in a natural setting; therefore, this makes the model we have developed more suitable to adapt during practical application [11, 12].

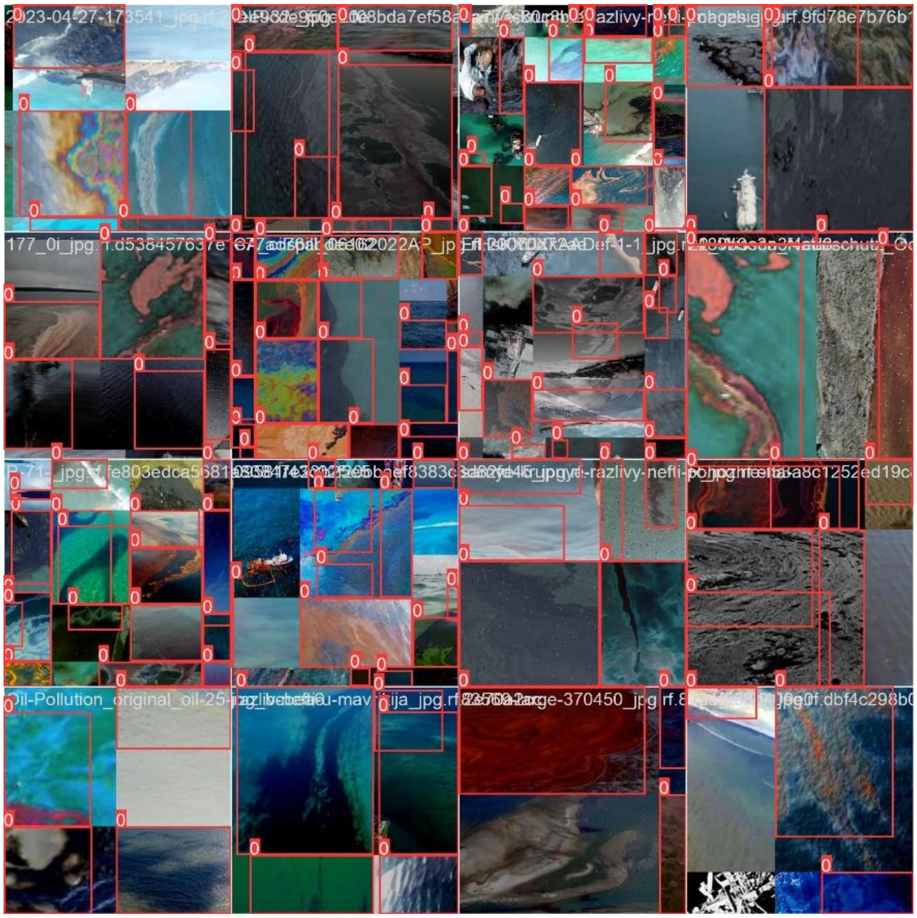


Fig. 1. Collected images used for model training.

Considering the possibility of the drone and satellite images taken from different angles, initially basic transformation methods are applied to the image set. These methods encompass horizontal and vertical conversion of the images and adjustments to light levels within the range of -25% to 0%, among others. During the training of the Machine Learning Models, it is recommended to split the dataset into three parts. Approximately 2400 images are used to train the model. Around 60 images from the test set will be used for testing the trained model and implementing necessary adjustments during the training of the model. Along with this, the validation set consists of 40 images that the model has not encountered before. The purpose of using the validation set is to ensure the accuracy of the trained model in real-case applications.

In Fig. 1, examples of images for model training are demonstrated. As depicted, Oil Leaks are not always in the same colours and shapes. This variability is observed across all images.

About the Model

The YOLO model is commonly used for real-time object localization in robotics, self-driving cars and video monitoring programs. There are numerous modifications and new architectures in the YOLO library, among them YOLOv8 is the most recent. Similar to other YOLO models, this model also includes Nano, Small, Medium, Large, and Huge Neural Networks [13].

Evaluation Metrics

F1 score is one of the commonly used metrics to check the model accuracy in Binary Classification problems. It provides insights into both the accuracy and reliability of the model.

$$F1 = \frac{2 * precision * recall}{precision + recall} \qquad (1)$$

Precision is the ratio of true positives (or true negatives) to total number of positive (or negative) predictions, while recall indicates the ratio of true predictions to the total number of samples in that class. Therefore, both precision and recall should be high to achieve a high F1 score [14]. We will investigate the impact of changes in precision and recall along with the F1 score.

Additionally, three loss functions should be explored for YOLO models.

Bounding Box Loss, also known as Localization Loss, measures the error between the predicted bounding box and the ground truth. The specified loss function employs relevant functions as regression models use.

The Confidence Loss measures the ability of the model to detect the presence or absence of an object. It penalties when the object is not detected, or it is detected multiple times, resulting in a high loss function value. This loss is determined by the overlapping area between the bounding box and the actual box.

The Class Loss function measures the error of probabilities assigned to each bounding box. The YOLO model assigns probabilities for each bounding box, and this loss function calculates the discrepancy between the predicted probabilities and actual ones, resembling the loss functions used in Classification Models [15].

Experimental

YOLO version 8 is utilized during the training of the model. Each of the Nano, Medium, Large and Huge Neural Networks used during training was retrained with 20-25 iterations.

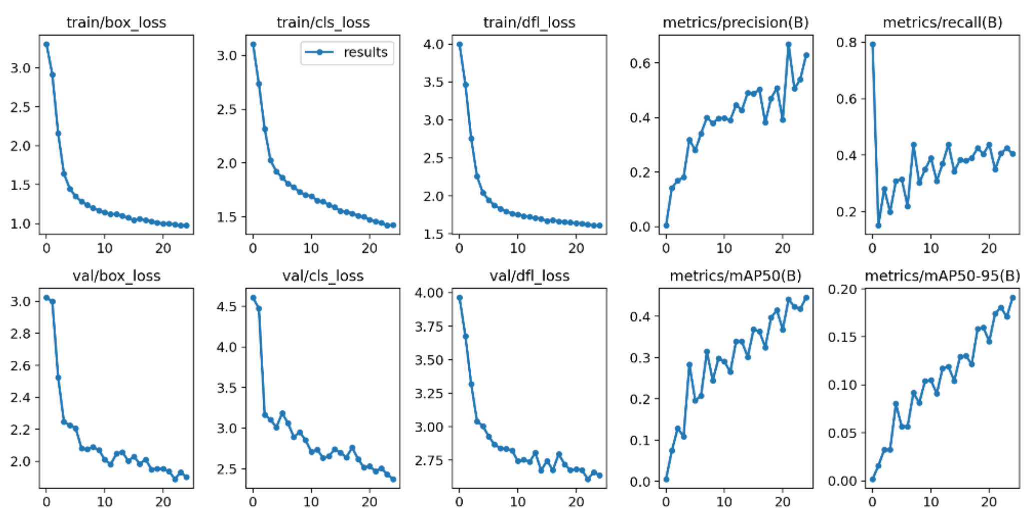


Fig. 2. Results of Small YOLOv8 Model Training.

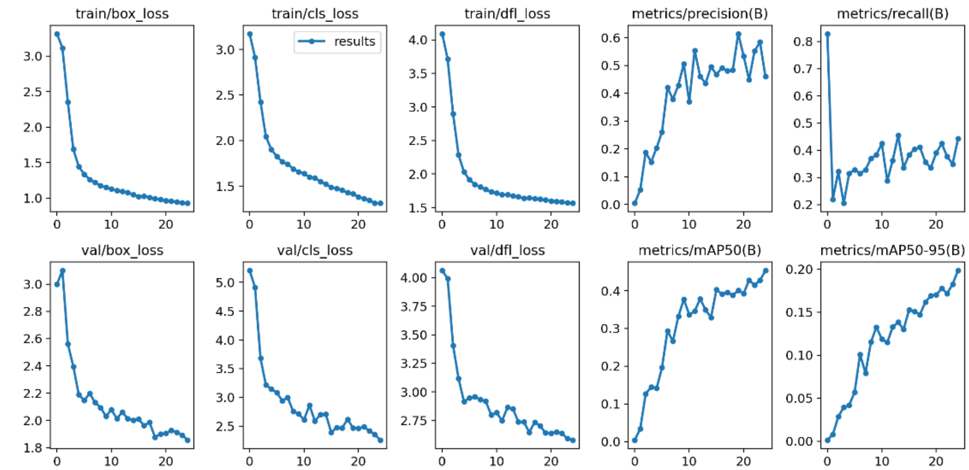


Fig. 3. Results of Medium YOLOv8 Model Training.

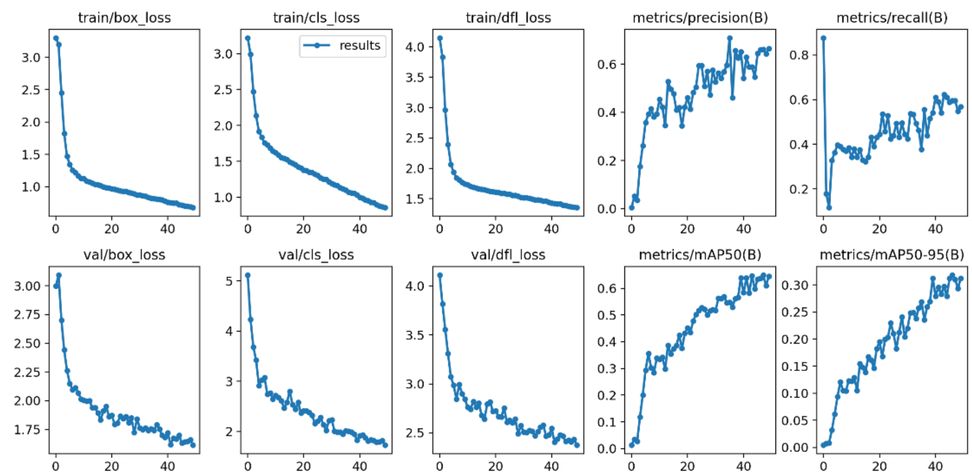


Fig. 4. Results of Large YOLOv8 Model Training.

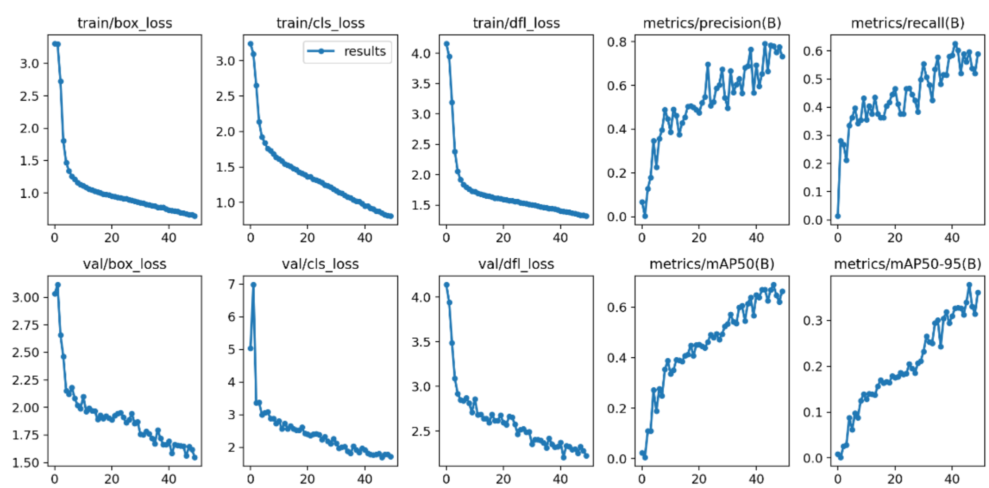


Fig. 5. Results of Huge YOLOv8 Model Training.

Based on the results of model training, the Large and Huge YOLOv8 models have superior performance in solving complex problems. For Nano, Small and Medium models, it is observed that precision increases while recall decreases. Furthermore, the mAP50 metric also shows a high value for the Large model. This refers to the potential for improvement of this model. With 50 iterations of training, there is a significant decrease in loss function values for both training and testing. This means it is possible to boost the efficiency of the model by increasing the number of iterations.

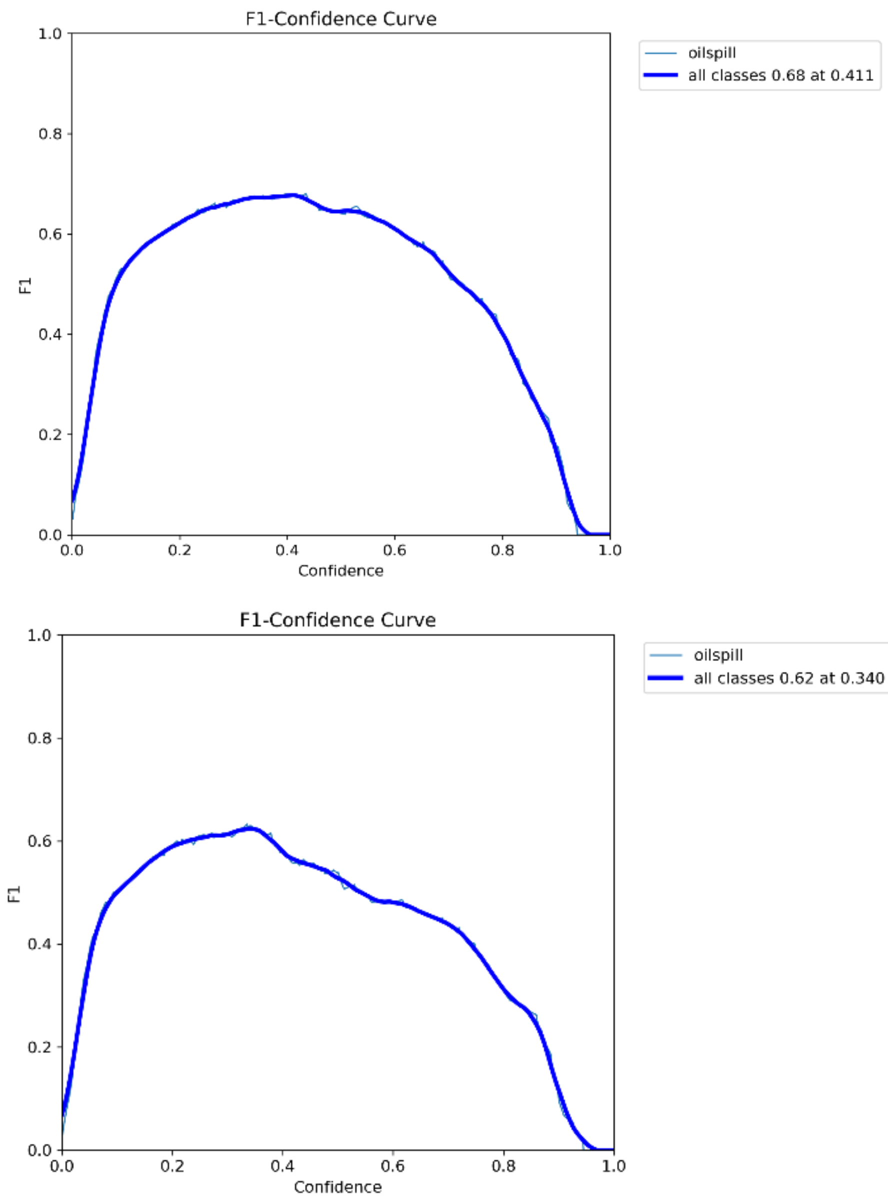
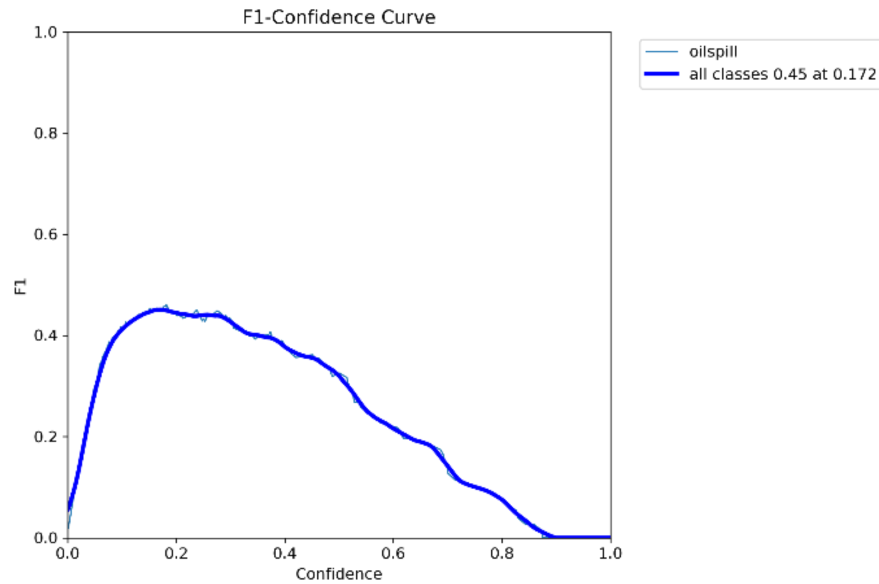


Fig. 6. F1 Confidence Curves for Large and Huge YOLOv8 models respectively.



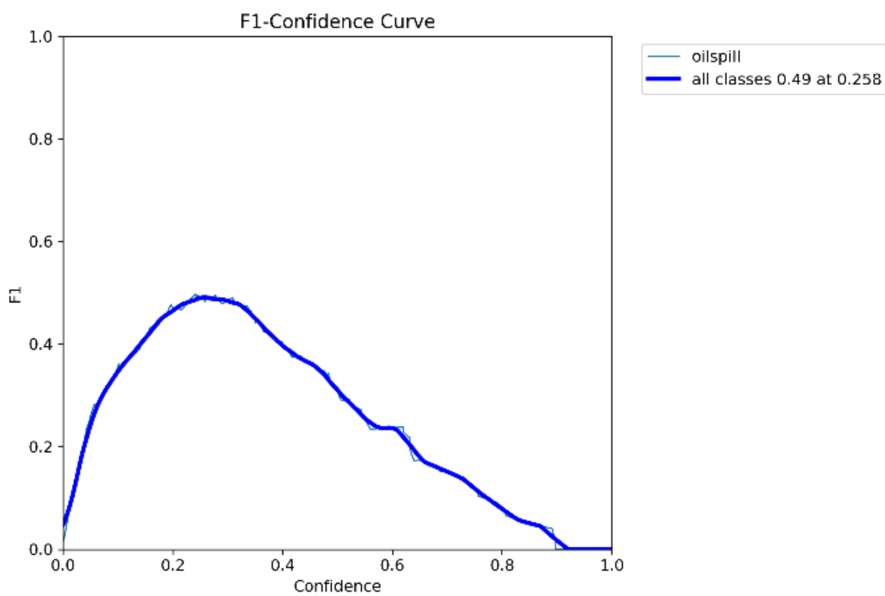


Fig. 7. F1 Confidence Curves for Medium and Small YOLOv8 models respectively.

According to the F1-Confidence Curve, the highest performance belongs to the YOLOv8 model with the Huge neural network, while the results of the Large model are slightly lower. In contrast, the performance of small and medium models is dramatically lower."

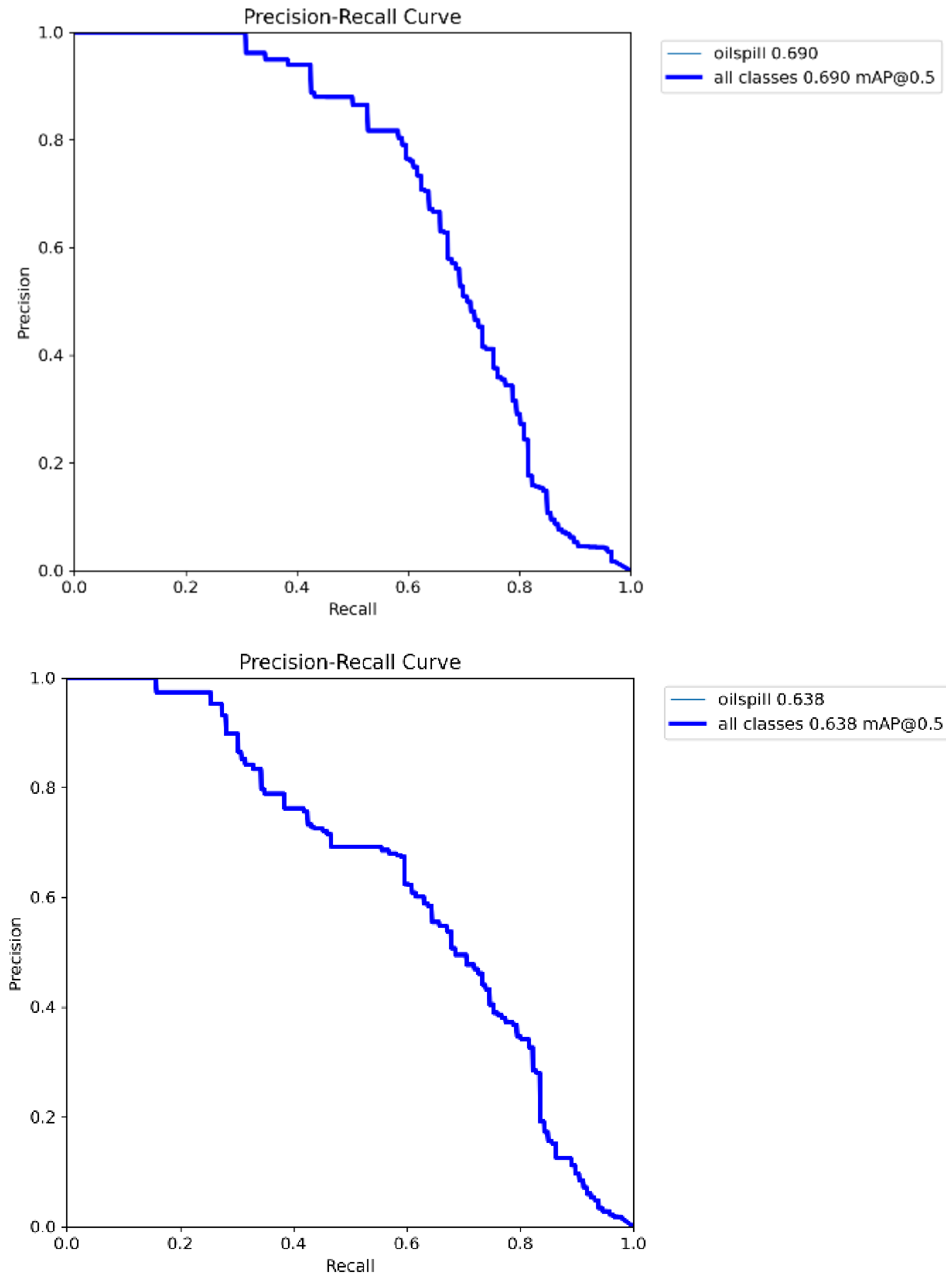


Fig. 8. Precision-Recall curve of Large and Huge YOLOv8 models respectively.

More area under the curve is considered a good result when analyzing Precision-Recall curves. The Huge type of model has better performance for this evaluation as well. The Precision-Recall curve provides the data about how much Precision should be compromised to increase Recall or vice versa. A higher evaluation signifies that we can have a model with high precision without losing recall value.

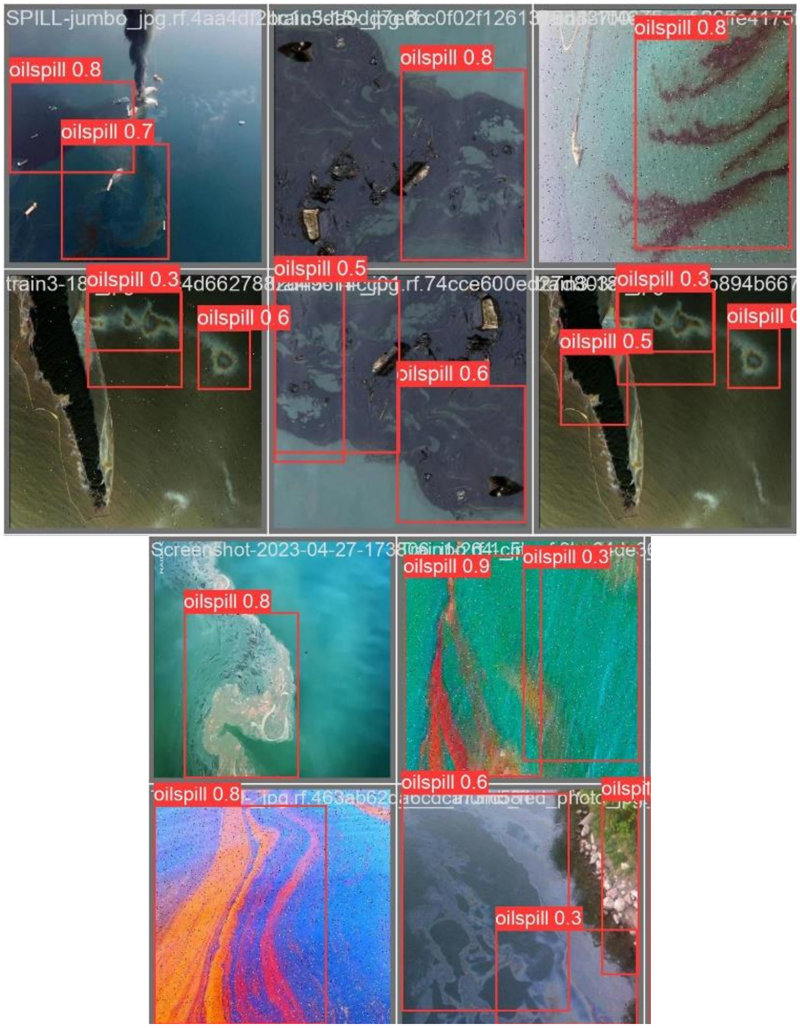


Fig. 9. Results of Testing of Huge Type of Model.

As shown in Fig. 9, the YOLOv8 model, which has a huge deep learning network, achieved high results with just 50 iterations.

Results

1. The YOLOv8_x model has been trained to detect oil leaks in photos captured by drones and satellites.
2. The latest models for this problem are checked and compared to each other.

References

1. Xudong Huang, Biao Zhan, William Perrie, Yingcheng Lu, Chen Wang. A novel deep learning method for marine oil spill detection from satellite synthetic aperture radar imagery. Marine Pollution Bulletin. June 2022, Volume 179, 113666. DOI:10.1016/j.marpolbul.2022.113666
2. Rami Al-Ruzouq, Mohamed Barakat A. Gibril, Am Shanableh, Abubakir Kais, Osman Hamed, Saeed Al-Mansoori, Mohammad Ali Khalil. Sensors, Features, and Machine

Learning for Oil Spill Detection and Monitoring: A Review. Remote Sensing. 2020, 12(20), 3338. DOI:10.3390/rs12203338

3. Nastaran Aghaei, Gholamreza Akbarizadeh, Abdolnabi Kosarian. GreyWolfLSM: an accurate oil spill detection method based on level set method from synthetic aperture radar imagery. European Journal of Remote Sensing. 2022, Volume 55, Issue 1, p. 181-198. DOI:10.1080/22797254.2022.2037468
4. Arnt-Børre Salberg; Øystein Rudjord; Anne H. Schistad Solberg. Oil Spill Detection in Hybrid-Polarimetric SAR Images. IEEE Transactions on Geoscience and Remote Sensing. 2014, Volume 52, Issue 10, p. 6521-6533. DOI: 10.1109/TGRS.2013.2297193
5. Fabio Del Frate, Andrea Petrocchi, Juerg Lichtenegger, Gianna Calabresi. Neural networks for oil spill detection using ERS-SAR data. IEEE Transactions on Geoscience and Remote Sensing. 2000, Volume 38, Issue 5, p. 2282-2287
6. Konstantinos N. Topouzelis. Oil Spill Detection by SAR Images: Dark Formation Detection, Feature Extraction and Classification Algorithms. Sensors. 2008, 8(10), p.6642-6659. DOI: 10.3390/s8106642
7. Fiscella B., Giancaspro A. Oil spill detection using marine SAR images. International Journal of Remote Sensing. 2000, Volume 21, Issue 18, p. 3561-3566. DOI:10.1080/014311600750037589
8. Suman Singha, Tim J. Bellerby, Olaf Trieschmann. Satellite Oil Spill Detection Using Artificial Neural Networks. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 2013, Volume 6, Issue 6, p. 2355-2363. DOI: 10.1109/JSTARS.2013.2251864
9. Jun-Hwa Kim, Namho Kim, Chee Sun Won. High-Speed Drone Detection Based On Yolo-V8. ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 04-10 June, 2023. DOI: 10.1109/ICASSP49357.2023.10095516
10. Аббасов В.М., Алиева Л.И., Абдуллаев Е.Ш., Талыбов А.Г., Исмайлов Т.А., Мамедханова С.А., Рзаева Н.Ш., Агамалиев З.З., Исмайлов И.Т., Мурсалов Н.И., Эфендиева Л.М., Джабраилзаде Ш.З. Реагенты и продукты для нефтяной, газовой, нефтеперерабатывающей и нефтехимической промышленностей. Баку, Издательство "Элм", 2016, 441 с.
11. Patrick Ebel, Yajin Xu, Michael Schmitt. SEN12MS-CR-TS: A Remote-Sensing Data Set for Multimodal Multitemporal Cloud Removal. IEEE Transactions on Geoscience and Remote Sensing. 2022, Volume 60, p. 25
12. Andrea Bisoffi, Claudio De Persis, Pietro Tesi. Controller Design for Robust Invariance From Noisy Data. IEEE Transactions on Automatic Control. 2023, Volume 68, Issue 1, p. 636-643
13. Juan R. Terven, Diana M. Cordova-Esparza. A Comprehensive Review of YOLO: From YOLOv1 to YOLOv8 and Beyond. Under review in ACM Computing Surveys. arXiv:2304.00501sun, 2 Apr 2023
14. André M. Carrington, Douglas G. Manuel, Paul W. Fieguth, Tim Ramsay, Venet Osmani, Bernhard Wernly. Deep ROC Analysis and AUC as Balanced Average Accuracy, for Improved Classifier Selection, Audit and Explanation. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2023, Volume 45, Issue: 1, p. 329 - 341
15. Tanvir Ahmad, Yinglong Ma, Muhammad Yahya, Belal Ahmad, Shah Nazir. Object Detection through Modified YOLO Neural Network. Scientific Programming. 2020, Article ID 8403262. https://doi.org/10.1155/2020/8403262

PEYK VƏ DRON ŞƏKİLLƏRİ VASİTƏSİ İLƏ DƏNİZƏ NEFT SIZMASININ SÜNİ İNTELLEKT MODELLƏRİ İLƏ LOKALLAŞDIRILMASI

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XÜLASƏ

Şəkil öyrənilməsi, dərin öyrənmə maşın öyrənmə alqoritmləri təbiətdə bir çox problemin dinamik bir şəkildə aşkar edilməsini mümkün edir. Tankerlər, neft buruqları və neft borusundan təbii karbohidrogen sızıntıları və dağılmaları dəniz ekosistemi üçün ciddi problem yaradır [1]. Praktikada bu tipli modellərin tətbiqi neft sızmalarının tez bir zamanda aşkarlanılmasında, alimlərə etdikləri təxminləri istiqamətləndirmsində, təmizləmə planlarını tərtib edilməsində, vaxtında və təcili qərarlar verilməsində və belə halların neqativ tərəflərinin dayandırılıb və azaldılması üçün istfadə edilə bilərlər. Son dövrlərdə məhz bu problem üzərində yüzlərlə məqalə dərc edilmişdir [2-7]. Qanunsuz çirklənmə davamlı monitorinq tələb edir və peyk vasitəsilə uzaqdan zondlama texnologiyası neft dağılmalarının operativ aşkarlanması üçün cəlbedici variantdır [8]. Bu məqalədə ən son modifikasiya edilmiş modellərin köməyi ilə bu problemin operativ həll edilməsi əməliyyatı icra edilmişdir [9]. Xüsusilə, biz nümunənin tanınmasında neft ləkələri və oxşar ləkələr arasında ayrı-seçkilik etmək üçün avtomatik yanaşmaların istifadəsinə diqqət yetiririk.

Açar sözlər: Neft, neft sızıntısı, süni intellekt, şəkil lokallaşdırma modelləri, PyTorch, YOLOv8.

ЛОКАЛИЗАЦИЯ УТЕЧЕК НЕФТИ В МОРЕ С ИСПОЛЬЗОВАНИЕМ СПУТНИКОВЫХ И ДРОННЫХ ИЗОБРАЖЕНИЙ С МОДЕЛЯМИ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА

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АБСТРАКТ

Алгоритмы компьютерного зрения, глубокого обучения и машинного обучения позволяют обнаруживать различные динамические проблемы в природе. Танкеры, нефтяные месторождения, нефтепроводы, утечки и разливы углеводородов создают серьезные проблемы для морских экосистем. [1] Использование этого типа модели может помочь оперативно обнаруживать утечки нефти, определять прогнозы ученых, составлять планы очистки, вовремя принимать срочные решения, а также останавливать или уменьшать

негативные последствия этих инцидентов. По этому вопросу в последнее время проведены многочисленные научные исследования [2-7]. Незаконное загрязнение требует постоянного мониторинга, а технология дистанционного отслеживания с использованием спутников является интригующим решением для обнаружения утечек нефти [8]. В данной статье решение этой проблемы представлено с помощью недавно обновленной модели [9]. В частности, подчеркните автоматический подход к различению марок масла и других подобных знаков.
Ключевые слова: нефть, утечка нефти, искусственный интеллект, модели локализации изображений, PyTorch, YOLOv8.