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# Research on the Detection Method of Crude Oil Leaking on Offshore Platform based on the Improved YOLOv5s Model

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## Abstract

**Aiming at the demand of crude oil leakage monitoring on offshore platforms, model optimisation and crude oil leakage target detection are studied based on the YOLOv5s model. The SE attention mechanism is introduced into the backbone network of the YOLOv5s model to enhance the model's learning of small crude oil leakage targets and suppress the background interference information. The deformable convolution module DCNv2 is introduced for controlling the sampling position of the convolution kernel to reduce the influence of irrelevant factors and further improve the detection accuracy of the model for small targets. The CIOU loss function of the original YOLOv5s is replaced with the EIOU loss function, which makes the model pay more attention to the difficult-to-detect targets and improves the detection accuracy of the model for crude oil spill targets. The longitudinal comparison experiments before and after the optimisation of the YOLOv5s model, as well as the cross-sectional comparison experiments between the optimised model and other typical models, confirm the superiority of the adopted optimisation method.**

## Keywords

**Crude Oil Leaking; Target Detection; YOLOv5s; SE Attention Mechanism; DCNv2; EIOU.**

## 1. Introduction

Crude oil leakage occurs from time to time during the operation of offshore platform equipment and systems, and early leakage that cannot be detected and handled in a timely manner is likely to result in serious consequences such as environmental pollution of the platform, marine pollution, and fire. Intelligent monitoring methods based on the combination of vision and deep learning can continuously monitor online, which is conducive to the detection and treatment of early leaks. For example, in 2019, Zhao et al. achieved situational awareness and intelligent alarm of dangerous phenomena at the production site through neural network algorithms such as Mask R-CNN in the field of deep learning for more than 10 material forms of runaway leakage phenomena at the production site of a coal-fired thermal power station [1].In 2021, Li et al. studied an intelligent detection system for runaway leakage at a power plant based on artificial intelligence technology, which The system adopts image analysis, sound analysis, temperature analysis and other methods to detect the leakage of oil, water, gas, steam, smoke, ash, coal and other on-site production equipment, and can accurately issue timely alarms. For high-temperature and high-pressure pipelines (main steam pipelines, reheat steam pipelines, water supply pipelines, etc.), the focus is on inspecting potential leakage areas such as welds, valves, flanges, elbows, tees, and sampling pipelines, to ensure that the intelligent detection system quickly and accurately identifies the runaway leakage [2].2022 Tian et al. developed an intelligent abnormal state identification and early warning system based on video data using artificial intelligent target detection algorithms, which was developed through the migration learning and small sample learning methods to improve the target detection YOLOv5 network

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structure in the field of deep learning, to analyse and identify the common phenomenon of running and leaking in the production site[3].

Analysing the above related research, it can be seen that there has been a certain amount of research on the detection of the phenomenon of running and leaking, but the recognition accuracy, as well as the richness of the dataset is still far from enough. Aiming at this problem, this paper takes the crude oil leakage detection on offshore platform as an example, and studies the crude oil leakage detection method based on YOLOv5 optimisation model.

## 2. YOLOv5s Model Structure

YOLOv5 is the 5th generation version of the YOLO sequence model, which is one of the most widely used deep learning models.YOLOv5 as a whole can be divided into four parts, the input (Input), the backbone network (Backbone), Neck, and the detection end (head) composition[4], YOLOv5s is a small model in the YOLOv5 series, its structural features are as follows:

(1) The Input part is mainly responsible for image preprocessing, normalising the input image, unifying the size and other operations. Mosaic data enhancement is to randomly crop, scale, and splice the four input feature images into one image to enrich the detection dataset, increase the robustness of the network, and reduce the burden on the GPU so as to improve the feature extraction accuracy and model inference speed.

(2) Backbone: This part is mainly composed of Conv, C3, and SPPF modules, which process the input image through a series of convolutional layers and pooling layers to gradually reduce the size of the feature map and increase the number of channels.

(3) Neck: this part is mainly composed of Feature Pyramid Network (FPN) and Path Aggregation Grid (PAN). Based on the features extracted from the backbone network, further feature fusion and up-sampling operations (Upsample) are performed to provide more advanced semantic information and the ability to adapt to different scales of images[5].

(4) Head: The Head section fuses and transforms features from different scales, which helps to capture higher level semantic information and contextual relationships to further process the extracted features and generate the final output[6].

Based on the performance of visual surveillance equipment, distance and environment, crude oil leakage may have problems such as small targets, partial occlusion, blurring, and uneven morphology. Experiments have shown that it is difficult to achieve ideal detection results by directly applying the YOLOv5s model. For this reason, the following method is used to optimise the YOLOv5 model.

## 3. YOLOv5s Model Structure

### 3.1. Introduction of the Squeeze-and-Excitation (SE) Attention Mechanism

Introducing SE (Squeeze-and-Excitation) [7]is a commonly used deep learning model optimisation technique, mainly used to improve the performance of neural networks on a variety of visual tasks, the core idea is to insert a Squeeze operation and an Excitation into the network.

The Squeeze operation reduces the feature map of each channel into a scalar to represent the importance of the channel, and eliminates the spatial information in the feature map by global average pooling, so that each channel contains only its most relevant information.

The Excitation operation receives the outputs of the Squeeze operation and computes that channel's attention weight based on those outputs to tell the network which channels are more important for the current task.

With the introduction of the SE module, the neural network can adaptively learn the importance of each channel and focus more attention on the features of the crude oil leakage, reducing the model's reliance on unimportant features and enhancing its ability to extract key features, thus improving the model's generalisation ability and robustness

## 3.2. The Loss Function is Replaced with EIOU

The loss function is used to measure the degree of deviation between the model's predicted value and the true value.The loss function used in the YOLOv5 model is by default the CIOU function, which takes into account three influencing factors, namely, the overlap area, the centre distance, and the aspect ratio.The CIOU function only reflects the difference in aspect ratio, which leads to the CIOU loss optimising the similarity in a way that is not always reasonable. In order to improve the model convergence speed and detection accuracy, the EIOU loss function improves the shortcomings of CIOU by changing its use of the distance and relative ratio of rectangular borders as the penalty term to the more direct use of the edge length as the penalty term, which minimises the difference between the width and height of the target frame and the anchor frame, thus producing faster convergence speed and better localisation results[8].

Based on the above analysis, this paper replaces the CIOU loss function of the original YOLOv5 with the EIOU loss function, so that the model pays more attention to the difficult-to-detect and easy-to-miss samples, thus improving the model's comprehensive detection of crude oil spills.

## 3.3. Introduction of the Deformable Convolution Module DCNv2

While conventional convolutional operations are fixed and the weights of the convolutional kernel are constant over the whole image, Deformable Convolutional Net-works (DCN) [9]introduces additional parameters to control the sampling position of the convolutional kernel. These extra parameters are usually learnt by a learning module and are also known as offsets. When performing deformable convolution, the sampling position of the convolution kernel is dynamically adjusted according to the content of the input feature map, thus enabling adaptation to the target shape. A modulated deformable convolution module[10]is introduced in DCNv2, which controls the offset of the convolution kernel sampling points while learning the weights of each sampling point, reducing the influence of extraneous factors and thus improving the model detection accuracy.

In order to ensure the detection accuracy of the crude oil leakage target, and at the same time reduce the number of parameters and computational volume of the model, the two C3 modules of the backbone network (backbone) feature pyramid fusion output of the YOLOv5s model are replaced with DCNv2.

## 3.4. Improved Overall Network Structure of YOLOv5s Algorithm

Based on the above optimisation methods, the SE attention mechanism is introduced into the backbone network of YOLOv5s model to reduce the model's dependence on unimportant features and enhance the extraction capability of key features; the C3 module in the backbone is replaced by a deformable convolution module to reduce the number of model parameters and computation volume, improve the target detection speed, and maximise the detection speed performance of YOLO; and EIOU is used to replace the original loss function of the model to make the model pay more attention to difficult-to-detect and easy-to-miss samples. EIOU to replace the original loss function of the model, so that the model pays more attention to the difficult to detect, easy to miss the detection of samples. The structure of the improved YOLOv5 model is shown in Figure 1.

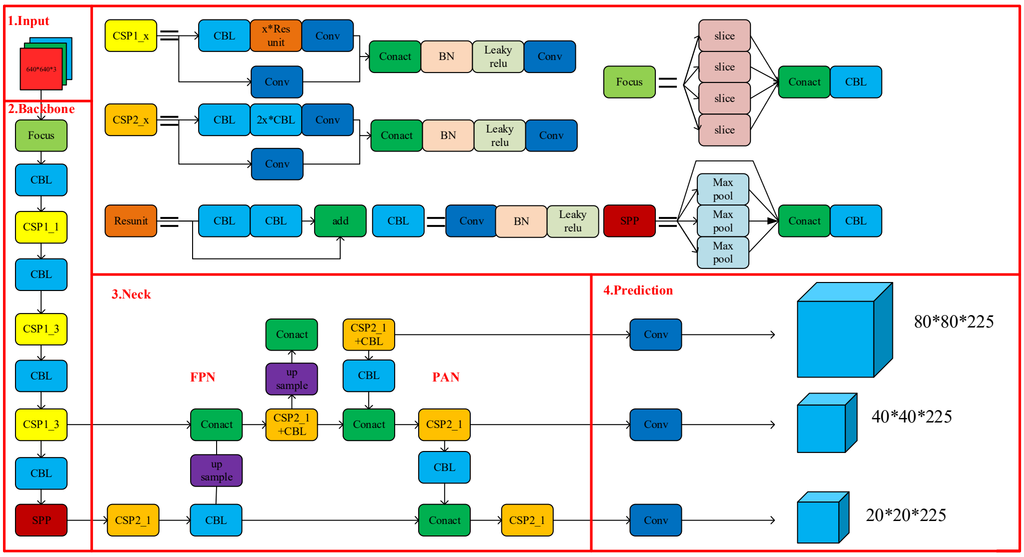


**Figure 1.** Improved YOLOv5 network structure

# 4. Offshore Platform Crude Oil Leakage Detection Experiment

## 4.1. Crude Oil Spill Dataset Construction

Currently, there is no open-source dataset available for the target of crude oil leakage, the paper obtains the real crude oil from the oil extraction port of the offshore platform, conducts the crude oil leakage experiments on the decommissioned Bohai Friendship FPSO, and captures a large number of crude oil leakage images in real scenarios. The dataset for deep learning model training, validation and testing was constructed.

In addition, in order to balance the robustness and generalisation of the model to the detection target, the dataset is expanded by image mirroring, rotating, clipping and scaling, contrast adjustment, brightness adjustment, masking, etc., to prevent overfitting during the training process due to insufficient sample data. The dataset contains a total of 792 crude oil spill images, and the number of images after using data enhancement is 3168. Using Labelimg tool for manual annotation as well as migration learning methods, the information accessed after annotation is a txt file in YOLO format, and the dataset is divided into training set, validation set and test set in the ratio of 6:2:2.

## 4.2. Evaluation Indicators

In order to evaluate the effectiveness of the crude oil spill detection model, the evaluation metrics used include accuracy P (Precision), recall R (Recall), average precision (AP, average precision), F1 score, FPS, and other metrics to comprehensively assess the model target detection performance. P reflects the proportion of all targets predicted correctly by the model; R reflects the proportion of all real targets predicted correctly by the model; AP is the area under the PR curve, which reflects the precision and stability of the model in detecting a specific category of targets.F1 score is the reconciled average of the two metrics of accuracy and recall.FPS is the number of frames per second of detected images, which is used to measure the model detection Speed.

## 4.3. Experimental Results and Analysis

In order to verify the superiority of the detection algorithm proposed in this paper, the experiment verifies the advantages of the DCNv2 module and the SE attention mechanism as well as the replaced loss function in the crude oil leakage detection and identification through ablation experiments, and the model training parameters are kept consistent, and the experimental results are shown in Table 1. Where YOLOv5 denotes the original model; YOLOv5-

V1 to YOLOv5-V4 are the experimental control group, and YOLOv5-D denotes the improved model in this paper.

**Table 1.** Results of ablation experiments for target detection

| modelling | CIOU | **EIOU** | CBAM | **SE** | **DCNv2** | P | R | F1 | AP |
|---|---|---|---|---|---|---|---|---|---|
| YOLOv5 | √ | | | | | 87.5% | 87.1% | 84.2% | 84.2% |
| YOLOv5-V1 | | √ | | | | 80.0% | 95.0% | 86.9% | 85.3% |
| YOLOv5-V2 | | | √ | | | 92.8% | 78.2% | 85.7% | 83.4% |
| YOLOv5-V3 | | | | √ | | 87.2% | 86.3% | 96.5% | 85.2% |
| YOLOv5-V4 | | | | | √ | 90.3% | 80.2% | 85.5% | 85.4% |
| YOLOv5-D | | √ | | √ | √ | 89.2% | 88.3% | 89.7% | 89.4% |

In Table 1, comparing the loss function of the original model, the AP value of the loss function model with EIOU is improved by 1.1% compared with the original model, indicating that the EIOU loss function makes the model pay more attention to some difficult-to-detect samples during training, thus improving the comprehensive detection performance of the model. Comparing the two attention mechanisms of CBAM and SE, the introduction of CBAM attention mechanism is not obvious, while the introduction of SE attention mechanism improves the AP value by 1% compared to the original model. In addition, the introduction of the deformable convolution module in the backbone network improves the AP value of the model by 1.2% compared to the original model, indicating that this convolution module improves the comprehensive detection performance of the model without increasing the number of model parameters and computation. The AP value of the improved model YOLOv5-D combining the above methods is improved by 5.2% compared to the original model. The detection results of the YOLOv5s model before and after the improvement on the same image respectively are shown in Fig. 2. From Fig. 2, it can be seen that the improved model improves the confidence level of the detection results significantly compared to the original model.


(a) yolov5s original model detection (b) Improved yolov5s model detection

**Figure 2.** Comparison of detection effect before and after model improvement

In order to further verify the superiority of the improved model in run-off detection, the improved model is compared with Faster-RCNN, YOLOv7, YOLOv8 and other models in the same experimental environment, and the experimental results are shown in Table 2.

**Table 2.** Comparison of the performance of the models

| modelling | P | R | $F_1$ | AP | FPS |
|---|---|---|---|---|---|
| Faster-RCNN | 35.4 | 70.6 | 48.3 | 64.4 | 13.8 |
| YOLOv7s | 86.1 | 74.7 | 75.3 | 76.7 | 50.8 |
| YOLOv8s | 86.4 | 86.3 | 79.5 | 80.9 | 68.3 |
| YOLOv5-D | 89.2 | 88.3 | 89.7 | 89.4 | 49.8 |

As can be seen from Table 2, the performance index of Faster-RCNN detection is significantly lower than that of other models, and the detection rate of the improved model is slightly reduced compared with YOLOv7 and YOLOv8, but the AP value is increased by 12.7% and 8.5% compared with the two control models, which further proves the advantage of the model improvement for the detection of crude oil leakage targets.Comparison of the effectiveness of the YOLOv7s, YOLOv8s and the improved YOLOv5-D model on crude oil leakage detection is shown in Fig. 3. The comparison of the effectiveness of the improved YOLOv5-D model for crude oil spill detection is shown in Fig. 3.

(a) Leakage-Original (b) YOLOv7s Detection (c) YOLOv8s Detection (d) Improved model detection

**Figure 3.** Comparison of the detection effect of different models

As can be seen in Figure 3, YOLOv7s and YOLOv8s failed to detect the crude oil spillage target below the graph, whereas for the more obvious target, all three models were able to detect it, but the improved model had a higher confidence level in the detection results.

## 5. Conclusion

Based on the demand of crude oil leakage target detection in visual surveillance, the paper investigates the optimisation of the YOLOv5s model and the target detection problem, and the main conclusions are as follows: the SE attention mechanism is introduced into the backbone network of the YOLOv5s model, which strengthens the model's ability of extracting key features. The deformable convolutional module is used to replace the two original C3 modules of the backbone network, which reduces the number of parameters and computation volume of the model while ensuring the accuracy of the network model. The CIOU loss function of the original YOLOv5 is replaced by the EIOU loss function, which assigns larger weights to the difficult-to-assign samples, thus making the model pay more attention to the difficult-to-detect samples during training. The superiority of the optimised model is confirmed by the method of ablation experiment and the experiment of comparing the detection effect of the optimised model with other similar models.

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