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APPLICATION OF COMPUTER VISION TO DETECT DEFECTS IN WELDS

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Abstract: In the context of increasing wear and tear of utility pipelines, improving the quality of diagnostics of their technical condition, as well as improving the quality of control over construction and repair work, is of particular importance. Timely detection of defects and damage helps prevent emergency situations and negative socio-economic and environmental consequences. Traditional methods of visual and instrumental control have a number of disadvantages, in particular, high labor intensity, long information processing time, and insufficient accuracy. This problem can be solved by using computer vision to identify and classify damage, which will improve the quality of defect detection, reduce the likelihood of human error, and speed up the diagnostic process. However, different levels of readiness of the developed machine learning algorithms require additional research to confirm the effectiveness of their use in professional fields, for example, when inspecting structures, which justifies the relevance of this study. The object of the study was the YOLO family of computer vision models capable of identifying various classes of defects. The aim of the study was to train the YOLOv5, YOLOv8, and YOLO11 detection algorithms and to perform a comparative analysis of their speed and accuracy of data processing using weld defects as an example. The results of the experimental studies show that the use of the latest version of the model does not lead to significant improvements in the quality of defect detection compared to previous versions. The results presented in the work allow us to assess the feasibility of using the new YOLO11 model to detect defects in radiographic images. Based on the experiments, researchers using computer vision methods to control the quality of welds can make an informed decision about whether to use this model or use previous versions of the algorithms.

Keywords: machine learning, lifecycle management, YOLO, radiography, predictive exploitation

ПРИМЕНЕНИЕ КОМПЬЮТЕРНОГО ЗРЕНИЯ ДЛЯ ОБНАРУЖЕНИЯ ДЕФЕКТОВ В СВАРНЫХ ШВАХ

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Аннотация: В условиях растущего износа трубопроводов коммунальной инфраструктуры особую значимость приобретает повышение качества диагностирования их технического состояния на этапе эксплуатации, а также повышение качества контроля строительных и ремонтно-восстановительных работ. Своевременное выявление дефектов и повреждений позволяет предупредить возникновение аварийных ситуаций и предотвратить негативные социально-экономические и экологические последствия. Применяемые традиционные методы визуального и инструментального контроля имеют ряд недостатков, в частности, высокую трудоемкость, длительное время обработки информации, недостаточную точность. Решение данной проблемы возможно путем применения компьютерного зрения для выявления и классификации повреждений, что позволит повысить качество обнаружения дефектов, снизить вероятность человеческих ошибок, а также ускорить сам процесс диагностирования. Однако разный уровень готовности разрабатываемых алгоритмов машинного обучения требует дополнительных исследований, которые подтвердили бы эффективность их применения в профессиональных областях, например, при обследовании сооружений, что обосновывает актуальность данного исследования. Объектом исследования данной статьи являлись модели компьютерного зрения семейства YOLO, способные определять различные классы дефектов. Целью исследования стало обучение алгоритмов детекции YOLOv5, YOLOv8 и YOLO11 и сравнительный анализ скорости и точности обработки ими данных на примере дефектов сварных швов. Результаты экспериментальных исследований показывают, что применение последней версии модели не приводит к заметным улучшениям качества детекции дефектов по сравнению с предыдущими версиями. Практическая значимость исследования заключается в том, что представленные в работе результаты позволяют выполнить оценку целесообразности использования новой модели YOLO11 для обнаружения дефектов на примере радиографических снимков. На основе проведенных экспериментов исследователи, использующие методы компьютерного зрения для контроля качества сварных швов, могут принять взвешенное решение о том, стоит ли применять эту модель или же использовать предыдущие версии алгоритмов.

Ключевые слова: машинное обучение, управление жизненным циклом, YOLO, радиография, предикативная эксплуатация

INTRODUCTION

According to Rosstat, the average wear and tear of utility networks in the country corresponds to an unsatisfactory technical condition. An increase in emergency situations is recorded, leading to a decrease in the quality of utilities, loss of resources, deterioration of the environmental situation and an increase in operating costs. Consequently, the quality of diagnostic measures during construction, repair, as well as during operational control directly determines the safety and uninterrupted functioning of the country's utility infrastructure. Particular attention should be paid to quality control of butt joints, where stress is most often concentrated, sealing elements wear out, and corrosion occurs. In our country, pipelines with welded seams are widely used, not only in utility infrastructure systems, but also for transporting gas, oil and other aggressive liquids. Given the difficult operating conditions, welded seams become one of the main sources of problems leading to accidents with serious socio-economic consequences.

To detect weld defects and prevent accidents, various methods of both visual and instrumental non-destructive testing are used [1-3]. The radiographic testing method has high accuracy and reliability of results compared to other methods. Defects in welds are determined during the study of welded joint images. However, this work is characterized by high labor intensity; therefore, automated radiographic scanning methods of welded joints are widely used in production. In this case, the main difficulty lies in processing and interpreting the radiography results, which requires exceptional attention and concentration of the specialist checking the images. Some defects may be barely noticeable even in high-quality images. In this case, there is a high probability that a non-destructive testing laboratory specialist will miss the defect.

Therefore, one of the ways to increase the reliability of weld diagnostics results, as well as the speed of data processing on radiographic images, is to use computer vision models to detect defects [4-6]. The latest scientific achievements in the field of artificial intelligence and parallel computing open up new opportunities for the use of computer vision models in various fields [7, 8], including construction and operation, to detect defects in welds [9, 10]. At the same time, different levels of technological readiness and market maturity of high-tech areas, as well as gaps in legislative regulation dictate the need to study emerging new products from the point of view of their effectiveness for practical application in the real sector of the economy.

Therefore, the objects of this study were the models of the well-known YOLO computer vision architecture, in particular YOLOv5, YOLOv8 and YOLO11. The hypothesis of the study was the assumption based on the developer’s data about the increase in the efficiency of the YOLO11 model compared to previous versions, considered on the example of processing weld inspection materials. The goal of the study was to perform a comparative analysis of the accuracy and speed of the YOLO family of models in solving the problem of detecting defects in welds on X-ray images. To achieve this goal, a list of research tasks was formed:

1) Preparing a training and test set of images with defects in welds;
2) Conducting an experiment to train YOLOv5, YOLOv8 and YOLO11 models on the training dataset;
3) Processing the results of the experiment and comparing the results of the models on the test dataset using standard metrics for assessing the quality of their work.

Literature Review

Improvement of the automated quality control system for welded joints can be based on both machine learning methods [11-13] and methods based on pixel brightness and geometric characteristics of welds [9, 14]. A review of studies of the most well-known machine learning algorithms allows us to assess their advantages and disadvantages for solving specialized problems. For example, the use of the SVM machine learning algorithm allows us to achieve fairly high accuracy, but small defects often remain undetected by the model [15]. The use of the AdaBoost algorithm has shown that it does not allow us to achieve high accuracy in detecting construction defects [16].

With the development of deep learning, convolutional models have increasingly been used to detect defects in welds [17, 18]. Quite high accuracy is observed when using the Faster R-CNN model, but the low image processing speed (7-10 frames per second) does not allow the model to be used to process a video stream [13, 19].

The YOLO deep learning model debuted in 2015 and has gained widespread adoption due to its high detection speed and the large number of versions released fairly quickly. The main difference between YOLO models and previous generation solutions [13, 19] is that they solve the detection problem in one stage. The model determines a set of bounding boxes based on the original image, while older approaches relied on pre-selecting candidate boxes from the image before feeding them to the model.

The model's operating principle is based on image processing by three consecutive blocks: Backbone, Neck, and Head [20]. Backbone transforms the image into a set of feature maps, which represent visual patterns of different levels. Neck simultaneously analyzes high-level and low-level patterns containing spatial and semantic information and obtains features for the final prediction of bounding boxes. The Head block is responsible for predicting bounding boxes and objects in them based on the features extracted by the Neck block. Each block, in turn, consists of standard layers used in computer vision: convolution layers (Conv) with batch normalization (BatchNorm) and activation functions (SiLU, Sigmoid, Softmax, etc.), pooling layers (MaxPooling), residual connections, etc.

And if the first YOLOv1 model solved only the detection problem, then subsequent models began to recognize more classes, with each modification the architecture of the model became more complex [19, 21-24]. Thus, in the YOLOv5 model [20] the emphasis was placed on optimizing computing resources, so it does not achieve such a high quality as its predecessors, but it works much faster, which allowed it to be used in real time.

In the YOLOv8 model, the architecture was optimized towards compactness. A significant change is the division of each branch of the Head block into two parts (Decoupled Head), one of which predicts the coordinates of the bounding box, and the other the class of the object located inside the box. This architectural change improves the convergence of the model and increases the quality of predictions. In [13, 25], a study of the YOLOv8 model for detecting defects in X-ray images was conducted, in [26], a technique for improving the quality of detection of this model was proposed.

The new YOLO11 model was presented in October 2024 [27, 28]. Modifications in this version affected both the optimization of computing blocks and the addition of quality improvement mechanisms [29]. A significant innovation was the addition of a new C2PSA (Cross Stage Partial with Spatial Attention) block with a spatial attention mechanism. Potentially, due to focusing on the most significant areas of the image, this block should increase the accuracy of object detection. For the latest version of the YOLO11 model, no studies were conducted on the quality of its operation in detecting defects in welded seams on X-ray images, which justifies the relevance of this study.

METHODS

Dataset

The dataset provided by the authors [19] was used to train the neural networks. The dataset is available at *https://github.com/huangyebiaoke/steel-pipe-weld-defect-detection* and is distributed under the GPL-3.0 license, which permits the use of data with a link to the original source. The dataset contains 3408 X-ray images of defects in pipeline welds.

The images represent 8 types of defects: slag inclusion, weld pores, crack, undercut, and build-up, lack of weld fusion, weld cavity, and arc rupture. Examples of images of each type of defect are shown in Fig. 1.

The number of images of each type of defect is given in Table 1. The weld seam in the images has different inclination to the image boundaries and different zoom levels. All images in the data set are marked.

Since training neural networks requires a large amount of data, the original data was supplemented with images obtained by transforming the original images, which is a common practice in training computer vision models.

The following transformations were used: horizontal and vertical reflection, rotation relative to the central point of the image within (-15°…+15°), brightness change in the range (-15%…+15%), and noise introduction for up to 1.05% of the image pixels. Several transformations can be applied to one image at once. Transformations preserve the original structure and content of images, since the changes are simple geometric and color transformations. Such image processing allows increasing the diversity in the dataset while preserving key visual features for training the model, which improves its ability to recognize and process real data, since it becomes more resistant to "extra" details in the image. After the addition, the dataset size was 7794 images. The Roboflow service was used to transform the images.

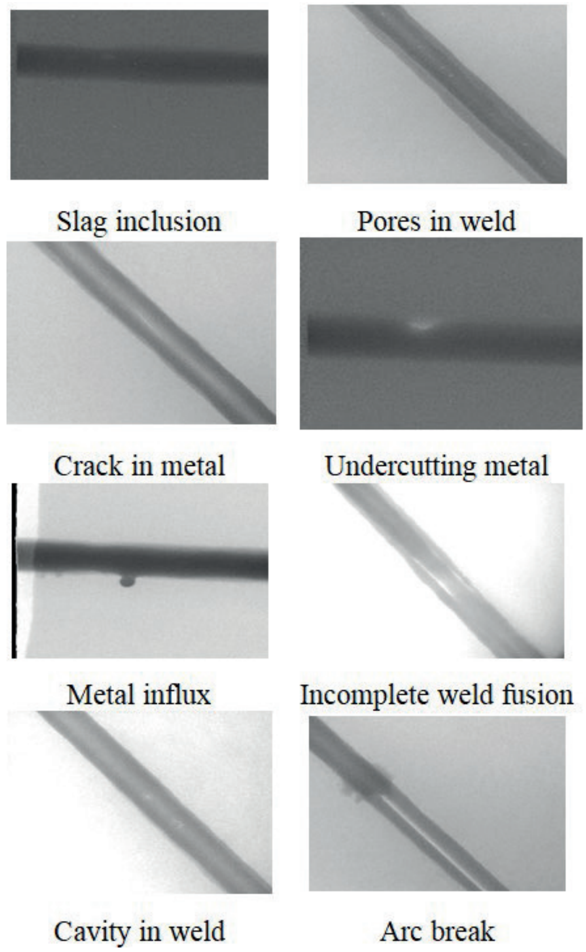

Figure 1. Examples of weld defects in images

Table 1. Number of images in the dataset for each type of defect

Name of defect	Number of images
Pores in weld	1339
Undercutting metal	35
Arc break	531
Crack in metal	119
Cavity in weld	613
Metal influx	219
Slag inclusion	136
Incomplete weld fusion	416

To speed up model training, the number of channels in the images was reduced from three (red, green and blue) to one (grayscale), which allows for faster model training without losing quality, since all images in the set are black and white. Also, to increase the speed of model training, the image size was reduced to 640×640 pixels.

Configuration of the experimental stand

The online services Google Colab and Roboflow were used to train the models, one Tesla T4 graphics processor with 16 GB of RAM was used. The following libraries were used to train the models: Ultralytics, Roboflow, IPython.

Three models were trained in the study: YOLOv5, YOLOv8 and YOLO11. YOLOv5 was trained to correctly compare the results of the models due to the lack of accurate data on image transformations in the training sample in the study [19]. The following versions of the models were selected due to the close number of parameters: YOLOv5m – 21.2 million, YOLOv8m – 25.9 million, YOLO11l – 25.3 million.

When training the models, the data were divided into training and validation sets in the following proportions: 10.4:1. The number of images in each set was: 6987 images for training, 672 images for validation, and 335 images for testing the model. The images were divided into groups in such a way that each group contained images of each type of defect. Each model was trained for 32 epochs (complete training cycles for all data). This number of epochs was chosen because it corresponded to the maximum duration of a session in the Google Colab service. The AdamW optimizer [30] was used for training. The parameters used in training the models are given in Table 2.

Table 2. Values of model parameters during training

Parameter	Value
learning rate	0.000833
momentum	0.9
batch size	16
warmup steps	3
dropout	0.0

Evaluation criteria

To determine the accuracy and completeness, the following object detection outcomes are introduced:

True Positive (*TP*) – correctly performed detection, i.e. the frame suggested by the model quite accurately coincides with the real frame established during image marking. The criterion for coincidence is the *IoU* (Intersection over union) area intersection coefficient:

$$IoU = \frac{Intersection\ area}{Union\ area} \tag{1}$$

where *Intersection area* is the area of intersection of the true and predicted frames; *Union area* is the area of union of the true and predicted frames.

At an *IoU* threshold of 50%, a model prediction is classified as *True Positive* if the calculated *IoU* value for that prediction is at least 50%.

False Positive (*FP*) – incorrectly performed detection, the model predicted an object where it does not exist, or the true and predicted frames do not match well enough and the *IoU* is below the threshold.

False Negative (*FN*) – incorrectly performed detection, the model did not detect the object in the image.

Next, the precision and recall indicators are calculated. Precision shows what proportion of objects predicted by the model are actually correct:

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

where *TP* is the number of true positives; *FP* is the number of false positives.

Recall measures what proportion of all real objects in the image were correctly detected by the model:

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

where *FN* is the number of missed objects in the image.
Next, the average precision for each defect class is calculated – Average Precision (*AP*). Among the class precisions, there is the mean Average Precision (*mAP*):

$$mAP = \frac{1}{k}\sum_{i}^{k} Precision_i \cdot Recall_i \qquad (4)$$

where *k* is the number of classes.
The standard metrics *mAP50* and *mAP50-95* were chosen as criteria for evaluating the performance of computer vision models. *mAP50* is the average accuracy among all classes, which is calculated at a fixed threshold of the *IoU* intersection rate ≥ 50%. *mAP50-95* is the average accuracy among all classes in the *IoU* range from 50% to 95% with a step of 5%. These indicators allow us to determine the ability of the model to detect objects of different classes, taking into account the accuracy and completeness of detection.
Using these metrics allows us to objectively compare models by assessing both their ability to accurately determine both the boundaries of a defect and the total number of correct and incorrect predictions.

RESULTS AND DISCUSSION

Comparison of model indicators

Based on the results of training the models over 32 epochs, graphs of changes in mAP50 and mAP50-95 were constructed on the validation sample (see Fig. 2 and 3).
Since in practice it is advisable to detect defects in welds at an *IoU* threshold of 50% or less, a more objective metric for the operation of models is *mAP50*. For comparison of models, metrics determined on the validation sample are provided, since it was not used in training.
Analyzing the graphs, we can conclude that after training, all models show very close results, while the *mAP* fluctuations during training are the smallest for the YOLO11 model. Also, the *mAP50* graph indicates that 32 epochs are sufficient for training and comparing models, since after the 25th epoch, there is a slight increase in the metric. Among the models considered, the highest defect detection speed was achieved by the YOLOv5 model. A comparison of the models' performance speed is given in Table 3.

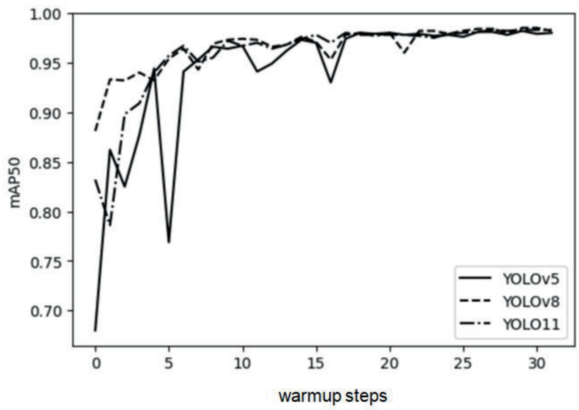

Figure 2. mAP50 values during validation during training

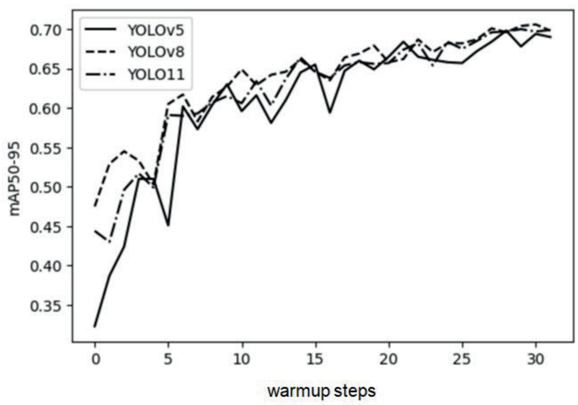

Figure 3. mAP50-95 values during validation during training

Table 3. Model operating speed

Model	Image processing time, msec	Processing frequency, images/sec
YOLOv5	16.4	61.0
YOLOv8	27.3	33.6
YOLO11	24.8	40.4

All models demonstrate an image processing rate of more than 30 images per second, which indicates the possibility of using any of them for video stream processing. The optimization of the YOLO11 model compared to YOLOv8 allows achieving a higher image processing rate. Table 4 shows the metrics calculated for the best-performing YOLO11 model training epoch.

Table 4. Best validation scores for the YOLO11 model

Name of defect (identifier)	***AP50***	***AP50-95***
Pores in weld (0)	0.933	0.437
Undercutting metal (1)	0.995	0.583
Arc break (2)	0.975	0.909
Crack in metal (3)	0.970	0.636
Cavity in weld (4)	0.979	0.812
Metal influx (5)	0.995	0.742
Slag inclusion (6)	0.995	0.662
Incomplete weld fusion (7)	0.994	0.749

Analyzing the results of the experiment, we can note the low accuracy of detection of pores in the weld, which may be due to their small size and low image clarity. For other defects, fairly close values of detection completeness and high accuracy are observed.

Figures 4-7 show examples of defect detection by the YOLO11 model in images from the test sample. In the upper left part of the frame around the defect in the image, the defect identifier (its number from 0 to 7) and the confidence of the model in determining this defect are indicated. It can be noted that the model quite clearly determines the position and boundaries of defects.

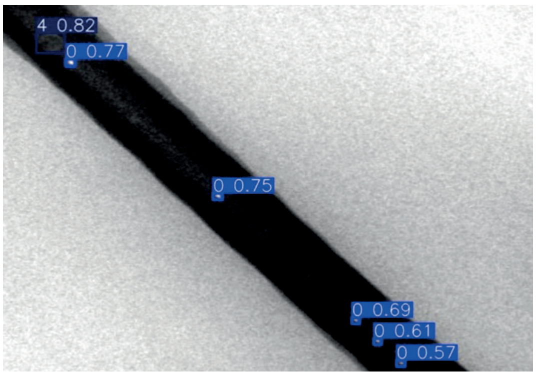

Figure 4. Detection by the model of a cavity (4) and pores in weld (0)

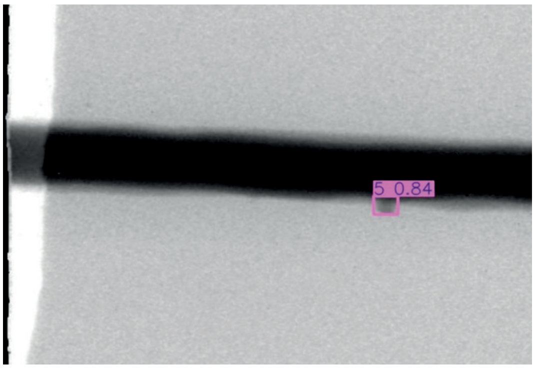

Figure 5. Detection of metal influx (5) by the model

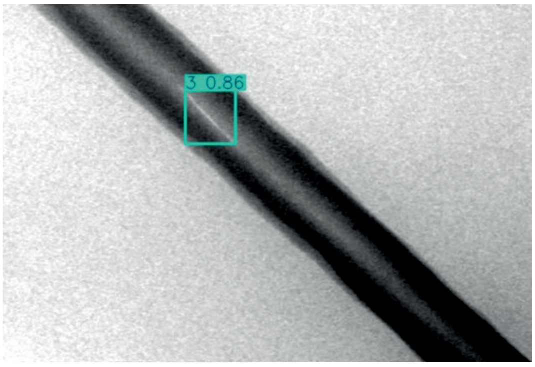

Figure 6. Detection of a crack in metal (3) by the model

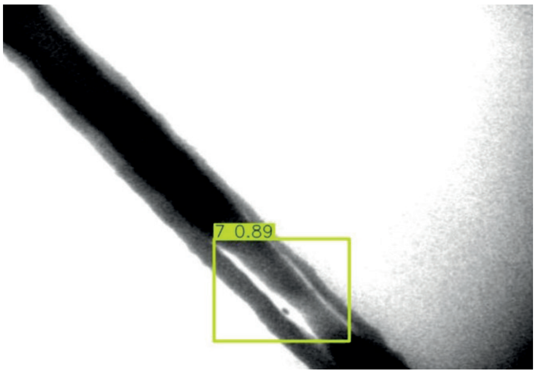

Figure 7. Detection of Incomplete weld fusion (7) by the model

In Tables 5 and 6 shows a comparison of the training results of the models.

The YOLOv8 model showed the greatest stability in class recognition. The training results show a more balanced detection of defects, since there is not such a big difference between the most poorly identified defects (pores in the weld and cracks) and the rest of the defects.

Table 5. Comparison of models by class recognition stability

Name of defect	***AP50***		
	YOLOv5	**YOLOv8**	**YOLO11**
Pores in weld	0.935	0,969	0.933
Undercutting metal	0.995	0.986	0.995
Arc break	0.986	0.983	0.975
Crack in metal	0.977	0.954	0.970
Cavity in weld	0.989	0.978	0.979
Metal influx	0.995	0.995	0.995
Slag inclusion	0.995	0.995	0.995
Incomplete weld fusion	0.994	0.995	0.994

Table 6. Comparison of mAP50 metrics based on model training results

Model	***mAP50***
YOLOv5	0.983
YOLOv8	0.985
YOLO11	0.979

Having analyzed the results of model training, we can conclude that the YOLO11 version shows slightly worse results, demonstrating the lowest *mAP50* value. The YOLOv5 and YOLO11 models are similar in *mAP50* metric values for each type of defect. The worst results shown by YOLO11 compared to other models may be due to the fact that this model relies on a spatial attention mechanism when forming a prediction, which allows it to focus on the most important areas of the image. In our case, it is impossible to distinguish the foreground or background in the image, and the defect can be anywhere along the seam. Also, the low quality of the model can be affected by modifications to the architecture aimed at increasing its speed.

CONCLUSION

1) Weld defect images were prepared for training the models, and geometric and color transformations were performed on the images to increase the diversity in the data set;
2) YOLOv5, YOLOv8 and YOLO11 models were trained for 32 epochs;
3) After training the models, a comparison of their performance results was carried out based on the standard metrics *mAP50*, *mAP50-95*, and a comparison of the image processing speed of each model was also performed.

The hypothesis put forward in the study, which is that the YOLO11 model will demonstrate better results in processing weld defect images than its predecessors, is partially refuted. The study shows that the best *mAP50* indicator in defect detection is achieved by the YOLOv8 algorithm. At the same time, the YOLO11 algorithm works slightly worse than other models, which may be due to the fact that the improvements made in the model cannot realize their potential in weld defect images. It is worth noting that the YOLO11 algorithm works 9% faster than the YOLOv8 algorithm.

Quality control of welded joints is carried out not only at the construction stage, but also at the operation stage. Regular automated control of welded joints can allow more accurate determination of the mechanism of change in the operational parameters of pipelines. Systematic acquisition of data on corrosion and defect formation in pipelines and their processing using effective computer vision algorithms will allow a transition to predictive operation, forecasting the service life of equipment and structures.

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