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AUTOMATION OF THE PROCESS OF SEGMENTATION OF IMAGES OF METAL SURFACE DEFECTS USING THE NEURAL NETWORK U-NET

АВТОМАТИЗАЦІЯ ПРОЦЕСУ СЕГМЕНТАЦІЇ ЗОБРАЖЕНЬ ДЕФЕКТІВ МЕТАЛЕВИХ ПОВЕРХОНЬ З ВИКОРИСТАННЯМ НЕЙРОННОЇ МЕРЕЖІ U-NET

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The paper deals with the task of automated segmentation of images of defects metal surfaces. The aim of the study is to improve segmentation algorithms using deep learning methods. The expediency of using the U-Net neural network, which is effective in the tasks of semantic image segmentation, is substantiated. With the help of a special architecture, the network can create segmentation masks with high efficiency. The training dataset for the neural network contained images of four classes of defects, including chips, cracks, and stains. As a result of analyzing the distribution of defect classes in the training dataset, it was concluded that the classes were unbalanced, which negatively affects the training results. To evaluate the quality of network training, a set of metrics such as Accuracy, F1 Score, and IOUScore is considered. The feasibility of using these metrics is analyzed, taking into account the features of the training data set. It is proved that under conditions of significant imbalance of classes, the Accuracy metric does not reflect the real quality of the model. The influence of different variants of the ResNet architecture backbone on the training results is analyzed. It is determined that the best results are shown by the ResNet18 model, which managed to obtain a Dice coefficient of 69 % and an IOUScore of 53 % on the test data set. It is proved that an increase in the number of model parameters does not always lead to an improvement in the reliability of the results. The article provides examples of test images and defect masks and countures predicted by the neural network. 13 Ref., 1 Tabl., 7 Fig.

У статті розглядається актуальне завдання автоматизованої сегментації зображень дефектів металевих поверхонь. Мета дослідження полягає у вдосконаленні алгоритмів сегментації з використанням методів глибинного навчання. Обґрунтовано доцільність використання нейронної мережі U-Net, яка є ефективною в завданнях семантичної сегментації зображень. За допомогою спеціальної архітектури мережа здатна створювати маски сегментації з високою ефективністю. Навчальний набір даних для нейронної мережі містить зображення дефектів чотирьох класів, включаючи відколи, тріщини та плями. У результаті аналізу розподілу класів дефектів у навчальному наборі даних зроблено висновок про незбалансованість класів, що негативно впливає на результати навчання. Для оцінки якості навчання мережі розглянуто набір метрик, таких як Accuracy, F1 Score та IOUScore. Проаналізовано доцільність використання даних метрик із врахуванням особливостей навчального набору даних. Доведено, що в умовах значної незбалансованості класів метрика Accuracy не відображає реальної якості моделі. Проведено аналіз впливу різних варіантів бекбону архітектури ResNet на результати навчання. Визначено, що найкращі результати показує модель ResNet18, за допомогою якої вдалося отримати значення коефіцієнту Дайса на рівні 69 % та показника IOUScore на рівні 53 % на тестовому наборі даних. Доведено, що збільшення кількості параметрів моделі не завжди призводить до покращення достовірності результатів. Наведено приклади тестових зображень та прогнозованих нейронної мережею масок і контурів дефектів. Бібліогр. 13, табл. 1, рис. 7.

Keywords: metal surfaces, image segmentation, neural networks

Ключові слова: металеві поверхні, сегментація зображень, нейронні мережі

Introduction. Defect detection is an important step in any product manufacturing and operation process. It helps ensure product quality and reliability and reduces the risk of negative consequences for users and manufacturers.

Metal products are widely used in various applications. Therefore, it is an urgent task to recognize their surface defects, which can significantly impair the quality and reliability of the product. Such defects can become an obstacle during the processing or use of the product, which can lead to emergencies and negatively affect human safety and health. Early detection of defects allows you to analyze the causes of their occurrence and make appropriate changes to production processes. This helps to improve the efficiency and cost-effectiveness of production, as well as reduce the percentage of waste. To improve the efficiency of defect detection and recognition, this process can be automated [1].

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There are various methods of metal surface inspection: visual, visual-optical, eddy current, ultrasonic, magnetic particle, etc. However, the visual-optical method is more productive in terms of inspection speed. For example, compared to the eddy current method, the visual-optical inspection method allows you to control a large area of the object with one camera image. This method is quite simple and cheap to use, requires simpler equipment than other methods, and can be applied directly on the production line.

There are different approaches to automating the process of detecting defects in camera images. One of them is detection, i.e. localization and classification of a defect by circling it in a rectangular box on the image. However, detection does not allow you to accurately determine the boundaries of the defect and does not provide information about its area, shape, and other parameters that may be important for further analysis.

Another approach uses image segmentation to more accurately identify the location of the defect and separate it from the defect-free area of the inspected object. As a result of the segmentation, special masks are superimposed on the image, which reflects the reliable prints or contours of the detected defects. The masks or contours can be painted with different colors that correspond to different classes of defects. The use of segmentation can help automate the defect detection process and reduce the time required to analyze a large number of images. This can be especially important in a production environment where you need to quickly and accurately identify defects to ensure high product quality.

Although there are various methods for segmentation, not all of them allow you to classify the detected objects. Given the rapid development of deep learning technologies, neural network models are the most promising option for automated segmentation tasks. It is neural networks that currently show the best results in the field of image processing [2].

Review of previous studies. The authors of [3] developed an experimental system for controlling rolled metal products capable of real-time operation in production conditions. The visual-optical control method is used. The illumination scheme of the product can be adjusted to optimize the contrast of various defects, depending on the surface roughness of the base material and defects. The good functioning of the illumination and especially its support in defect recognition has greatly simplified image analysis algorithms. Defect recognition is based on the analysis of blobs (binary large objects) in images. The authors found that the classification process using statistical methods is complicated by large variations in different types of defects and the lack of accurate models for their shape. The classification of larger defects, such as longitudinal and transverse scratches, works well. But the system is not reliable for defects consisting of several small defects, such as spills. Also, the disadvantage of all statistical methods is low resistance to interference, low versatility, and poor generalization properties.

In article [4], a new approach is proposed aimed at increasing the reliability of corrosion damage segmentation results using traditional methods. The segmentation results are negatively affected by uneven illumination, protective coating similar to the corrosion colors, and the presence of corrosion spots. Each of these factors can cause over- or under-segmentation of the corrosion damage area. The authors propose an intelligent digital image processing algorithm for segmenting corrosion defects on painted steel surfaces. After image preprocessing, an alpha-matting procedure is applied. This procedure uses segmentation with a Gaussian mixture model.

The proposed method creates visible image distortions around the shadow boundaries. A similar problem occurs when detecting corrosion spots using alpha matting. This problem is partially solved by selecting some threshold values. However, this approach is only effective for small image areas, as different areas of the image may require different thresholds for proper segmentation. In addition, the proposed method for detecting corrosion on a red background has a high probability of error for images that contain only corroded or only undamaged areas.

In work [5], computer vision technologies are proposed for detecting defects on metal surfaces. The approach uses the architecture of deep convolutional neural networks for segmentation. The overall segmentation model uses various image preprocessing and post-processing techniques to optimize the algorithm to make it practical for use. The system accurately segments the defective areas and has a classification accuracy of 93.46 %, even if the images contain many distortions. Qualitative and quantitative analysis confirms the performance of the algorithm. Another advantage of the proposed model is that it can be easily redesigned to solve similar problems of segmentation of other objects with minor modifications to the algorithm.

At the same time, the system under consideration is designed to segment images of only one type of defect - metal cracks. This is a disadvantage since it is often necessary to detect and classify more than one defect. Therefore, there is a need to develop a neural network that can segment images with several different types of defects.

To solve the problem of detecting atypical defects, the authors of [6] introduce a hierarchical method for classifying and detecting defects in steel surfaces. The proposed approach uses a hierarchical structure for dividing objects into two classes at the first stage, and object detection and semantic segmentation algorithms

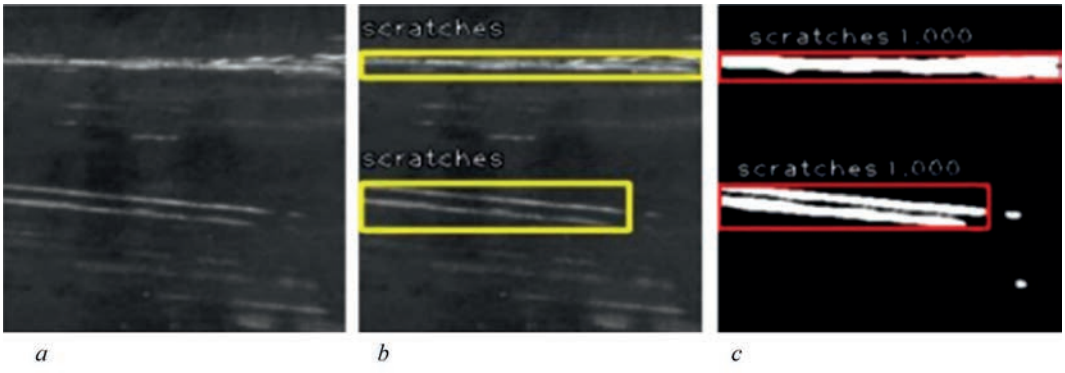

Fig.1. Detection of defects in the form of scratches: *a* — input image; *b* — annotation of the input image; *c* — output image

at the second stage. It demonstrates a mean accuracy rate (mAP) of 77.12 % in detecting surface defects.

An example of the detection result and the generated defect map on the test data are shown in Fig. 1. In the figure, you can see the input image, the corresponding ground truth (GT) annotation, i.e. the correct answers to the input image, and the final image predicted by the neural networks. The similarity between the predicted image and the GT annotated image is obvious. Also, the model was able to detect faint scratches, although the annotation did not provide information about them.

The disadvantage of this development is that classification and segmentation are performed by two separate neural networks. This architecture is complicated because instead of one network, two need to be trained. This significantly reduces the adaptability of the system and the requirements for the training dataset. In addition, the authors point out that some defects still cannot be detected because the difference between the defect and the background is not clear. The defect detection is also complicated by the disadvantage of the chosen network architecture for detection, namely the limited set of anchor boxes.

Thus, an urgent task is to improve the method of segmenting images of metal surface defects. In particular, it is promising to use a single neural network, the architecture of which will be devoid of the disadvantages discussed in the analytical review.

Statement of the problem. This study aims to improve algorithms for automated segmentation of images of surface defects of metal surfaces. Such a system should automatically detect the location of defects, determine their contours, and classify them by type. The input images of the object under inspection are received by the intelligent digital processing unit from a special camera installed on the production line or directly above the product. The output of the system is an image with highlighted contours of the detected defects. The color of the contour corresponds to a certain class (type) of the defect.

Based on the above review of existing works, segmentation methods based on deep learning are promising. The developed automated segmentation algorithms should have no less efficiency and reliability than existing analogs. The system should be free of the architectural limitations discussed earlier and be flexible and convenient for practical use in industrial environments.

Description of the model for segmentation. To date, the best results in image segmentation tasks are demonstrated by the U-Net neural network [7]. This network has a special convolutional architecture op-

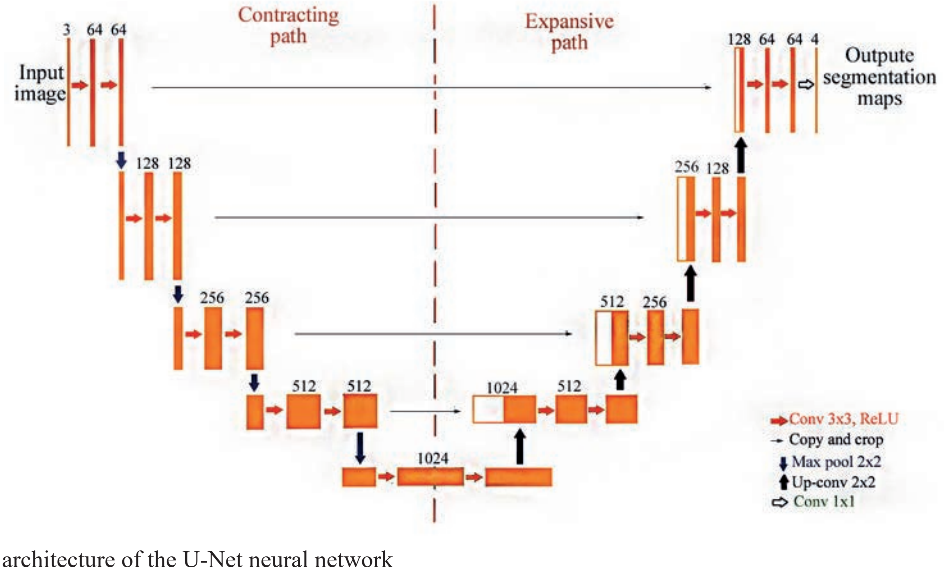

Fig. 2. The basic architecture of the U-Net neural network

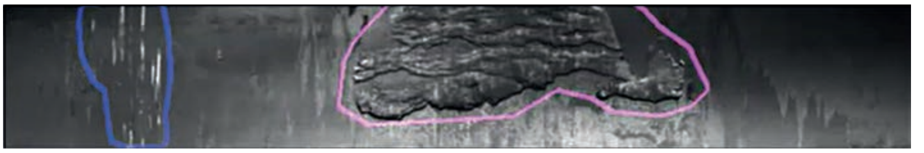

Fig. 3. Example image from the training dataset

timized for semantic image segmentation (Fig. 2). Its main idea is that the network has two data paths: contracting and expansive. The contracting path is responsible for reducing the size of the image and obtaining its abstract features - diagnostic features. The expansive path is designed to restore the original image size and accurately recreate the segmentation mask.

The contracting path consists of several consecutive convolutional layers with the ReLU activation function, as well as a max pool subsampling layer. This process reduces the image size and helps to select the most important informative features.

Expansive path layers contain up-sampling operators that increase the size of feature maps. After that, convolutional layers are used to reduce the number of feature channels. Then, using concatenation with the corresponding feature maps from the contracting path, the network tries to preserve the details of the input image and refine the segmentation masks.

The last layer in the network is a convolutional layer with 1×1 filters, which reduces the number of channels to the number of classes that the network determines. For example, if the network defines two classes, the last convolutional layer will return two channels. Each channel will contain a segmentation mask for the type of defect it defines.

In general, U-Net can restore images with high confidence [8]. The U-Net method also uses «skip-connections» that provide information transfer between different layers of the network. This allows for more efficient use of information from different resolution levels and helps to avoid the problem of losing context from small details.

U-Net's packetized blocks are organized in the form of backbones [9]. A backbone is a basic architecture used to build more complex networks. Most often, the ResNet architecture is used as a backbone in the U-Net network. In this case, the architecture of the contracting path of the U-Net network will be identical to the ResNet architecture. And the expansive path will be an inverse copy of the ResNet network. The computing power of the network varies depending on the complexity (depth) of the backbone.

Description of the training dataset. To train the neural network model, we used an open dataset from Severstal [10]. This is a ready-made set of images created using high-frequency cameras for the training and validation of neural networks. An object in each image may have no defects, a defect of one class, or several defects of different classes. In total, there are 4 different classes of defects in the images, namely: multiple chips, a single vertical crack, multiple vertical cracks, and multiple large patches on the surface. The mask for each class of defects is encoded in a single line, even if there are several unrelated defective areas in the image. The dataset contains 12568 images for training and 5506 images for testing. The material in the images used to train and test the neural network is steel. The shooting conditions are unknown. The resolution of the images is 800×128 pixels.

To reduce the size of the annotation file, a special way of encoding the length of the pixel value sequence is used. Instead of providing an exhaustive list of indices for segmentation, pairs of values containing the starting position and length of the sequence are provided. For example, '1 3' means that starting from pixel 1, 3 pixels (1, 2, 3) should be considered. Thus, the code '1 3 10 5' means that pixels 1, 2, 3, 10, 11, 12, 13, 14 should be included in the mask. The encoding algorithm additionally checks that the number pairs are sorted, have positive values and that the decoded pixel values are not duplicated. The pixels are numbered from top to bottom, then from left to right: pixel 1 is pixel (1,1), pixel 2 is pixel (2,1), and so on. Fig. 3 shows an example with defects of the third and fourth classes, each of which is highlighted by a contour of a certain color.

Fig. 4 shows a graph that displays the distribution of defect classes in the training dataset. Analyzing the graph, we conclude that the classes are not balanced. The majority (77.3 %) of the images contain a third-class defect and only 3.7 % contain a second-class defect. The imbalance of classes is caused by the fact that during production, some defects occur much more often than others. And some, on the contrary, occur quite rarely. Therefore, it is not possible to take more images of, for example, a second-class defect.

Description of metrics for segmentation. The segmentation task requires the use of specialized metrics that should take into account both the accuracy of the obtained defect masks and the quality of classification. The classical accuracy metric reflects the proportion of correctly classified pixels relative

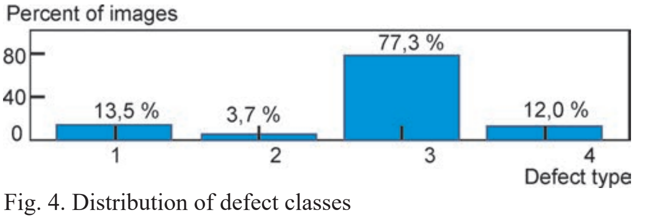

Fig. 4. Distribution of defect classes

to the total number of pixels in the dataset. For example, if the model classifies 90 out of 100 pixels correctly, the accuracy will be 90 %. The disadvantage is that this metric does not work well for unbalanced classes [11].

More reliable estimates can be obtained using metrics based on the assessment of first- and second-order errors. Thus, the precision metric reflects the proportion of correctly classified defective pixels relative to all pixels that the model has assigned to the defective class. For example, if the model classifies 100 pixels as defective, 80 of them are really defective, and 20 are identified incorrectly, then the precision will be equal to 80 %.

Recall is a metric that measures the proportion of defective pixels detected by the model in relation to the total number of pixels that are actually defective. Recall evaluates how efficiently the model finds defective pixels.

For the final evaluation of the classification quality, F1 Score is usually used. This metric allows you to assess the balance between precision and recall. F1 Score is maximized when precision and recall have the same high value. This means that the model is equally good at detecting and classifying defective pixels. This indicator is calculated by the formula:

$$\text{F1\_Score}=\frac{2\left(\text{precision}\times\text{recall}\right)}{\left(\text{precision}+\text{recall}\right)} \qquad (1)$$

If you use the F1_Score metric to evaluate the quality of segmentation, the formula for calculating it looks like this:

$$\text{F1\_Score}=\frac{2\times\left|X\cap Y\right|}{\left(\left|X\right|+\left|Y\right|\right)}, \qquad (2)$$

where |X| and |Y| are the number of elements in the samples X and Y, respectively, |X∩Y| is the number of common elements in the samples X and Y. In our case, X is the annotated pixels from the training dataset, Y is the pixels processed by the neural network. The F1 Score metric presented in this form is called the Dice coefficient [12]. The Dice coefficient takes values from 0 to 1, where 0 means a complete absence of common elements, and 1 means a complete match between the samples.

Another metric for evaluating the quality of segmentation is the IOU (Intersection over Union) or Jaccard index. It reflects the ratio of the intersection area of the predicted mask and the true mask to the area of their union. Intuitively, IOU can be interpreted as a measure of similarity between the predicted and true masks. This allows you to evaluate the reliability of the model segmentation for a particular image, as well as to make a generalized assessment of the quality of the model segmentation for the entire dataset.

In practical applications, modified versions of IOU are often used, such as Mean IOU or IOU Score, which are calculated for the entire dataset and allow us to obtain a generalized assessment of the quality of model segmentation. IOU Score is calculated as the average IOU value over all images in the dataset. This metric is usually used in multiple segmentation tasks when each image contains several classes of objects, which is suitable for assessing the quality of the network with the proposed U-Net architecture.

Results analysis. Figure 5 shows a graph of the model training using ResNet18, which illustrates the change in the Dice coefficient over 30 epochs. The following settings were chosen for training: activation function – ‘sigmoid’ (converts any input signal into a range of values from 0 to 1), optimizer – ‘adam’ (adaptive gradient descent optimization method), loss function – ‘binary_crossentropy’ (used to determine which of the two classes a given input element belongs to).

During the training, five different variants of the ResNet architecture backbones were tested. The averaged results of the network using each of the backbones are shown in table. At first glance, the accuracy parameter shows incredibly good results. However, when calculating this parameter, the background class that occupies most of the image is taken into account. This leads to a critical imbalance of classes, which makes the accuracy metric unreliable for these conditions [11].

The best results are shown by the model using the Resnet18 backbone, which has a Dice coefficient of 69 % and an IOUScore of 53 %. At the same time,

Comparison of the results of different backbones

Backbone	Params	Acc	Dice	IOUScore
Resnet18	11M	0.9922	0.6912	0.5306
Resnet34	21M	0.9923	0.6724	0.5092
Resnet50	23M	0.9920	0.6721	0.5088
Resnet101	42M	0.9922	0.6744	0.5112
Resnet152	58M	0.9921	0.6660	0.5024

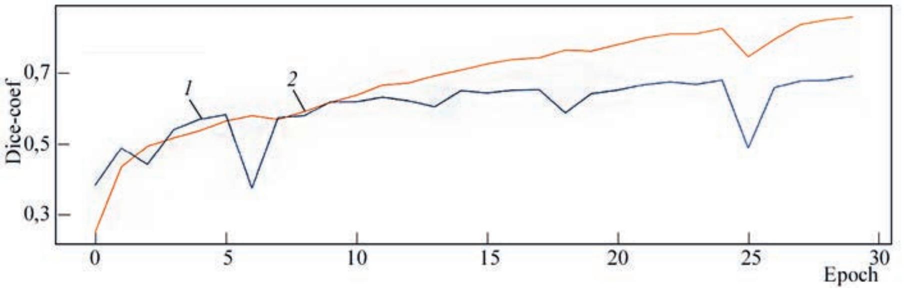

Fig. 5. Graph of Dice coefficient changes during epochs using the ResNet18: *1* – val-dice-coef, *2* – trn-dice-coef

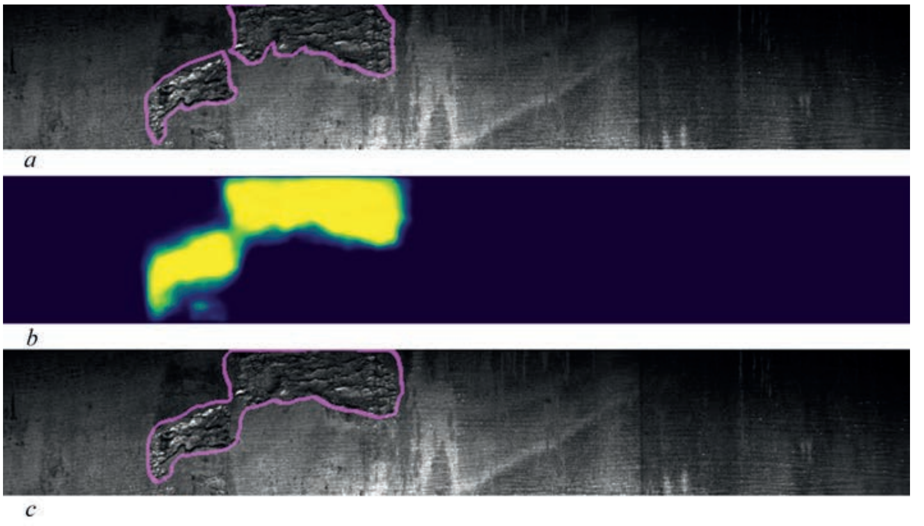

Fig. 6. Testing of the neural network: *a* — annotated image from the training dataset, *b* — mask at the output of the neural network, *c* — predicted defect contour

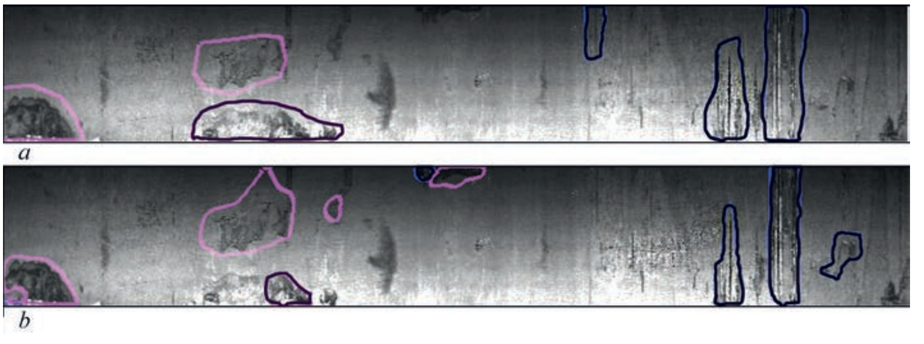

Fig. 7. Examples of image segmentation with defects: *a* — correct contours from the training dataset, *b* — contours predicted by the neural network

this model has the smallest number of parameters. That is, it will take much less time to train it compared to more complex backbones. The worst results were obtained for the ResNet152 backbone, although this network has the largest number of parameters.

Table shows that quite significant changes in the number of parameters have little impact on the quality of the model. Thus, it can be concluded that increasing the number of model parameters does not always lead to an improvement in its efficiency. In addition, the table shows that all the models under consideration have a Dice coefficient value of up to 69.12 %. This means that the resulting segmentation masks are reliable. The reliability of the segmentation is also evidenced by the relatively high value of the IOUScore [13].

Fig. 6 shows examples of annotated images for testing and the corresponding masks and defect contours predicted by the neural network. In the process of processing the original image, masks are first predicted (Fig. 6, *b*), which are then filtered by threshold level to obtain defect contours (Fig. 6, *c*). Comparing the contours of the defect detected by the network with the annotated contours (Fig. 6, *a*), we can conclude that the segmentation quality is high. This is confirmed by the quantitative indicators discussed earlier.

Fig. 7 shows a test image with defects of two different classes. Comparing the annotated image (Fig. 7, *a*) and the one predicted by the network (Fig. 7, *b*), we can see that the model found all the defects that are present on the surface. At the same time, some areas were mistakenly labeled as defective. The classes of correctly detected defects are correctly identified by the system.

Conclusions

According to the results of the analytical review, the prospects of improving the methods of automated image segmentation for detecting defects in metal surfaces by the visual-optical method have been established. The use of deep learning models has several advantages over classical segmentation methods. This provides greater control efficiency and higher system adaptability compared to traditional approaches.

It has been determined that the U-Net architecture currently demonstrates high-quality results in the segmentation of images with surface defects. For the used dataset, the Dice coefficient was obtained at the level of up to 69.12 % and the IOUScore up to 53.06 %. Additionally, we compared different backbones to determine the impact of their complexity on the overall performance of the model. The results showed that more complex backbones do not provide higher control reliability.

Among the existing limitations, we can highlight the fact that training a neural network requires a large number of annotated images of metal surface defects. An insufficient number of images or their low representativeness leads to a deterioration in the quality of segmentation, which is a common drawback for all deep learning models. The use of the U-Net neural network may have limitations in the quality of segmentation if the defects on the metal surface are more complex than those on which the network was trained.

One possible area for further research is to improve the architecture of the neural network to improve the values of the obtained metrics. It is also interesting to investigate the possibility of using other types of neural networks or their hybrid models. Another important task is to expand the training data set. In particular, increasing the resolution of images, increasing the number of defect classes, and the quality of their annotations.

Due to the high adaptability of this method, we can consider using it for other purposes in the future. For example, for automated segmentation of defects on other types of surfaces. The use of neural networks in automated image segmentation has great potential for application in many fields, including medicine, industry, transportation, and many others.

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