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# Semantic segmentation in flaw detection

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**Abstract**. The paper presents a review of study on detection and classification of defects using semantic image segmentation based on convolutional neural networks. Taking into account the revealed general features of flaw detection tasks of various industries related to the lack of a large marked data set and the need to detect defects of small sizes. The convolutional neural network of the u-net architecture was chosen as the basis for the decision support system. Testing of this architecture on several datasets yielded positive results regardless of the area of use.

## 1. Introduction

Flaw detection requires a wide range of appropriate description methods and means of control of materials and products. Despite the diversity of physical principles used in the basis, many technical solutions consist of two stages: image acquisition and its analysis in order to detect any deviation from the specific characteristic. In some cases, it is not enough only to detect deviations; it is important to detect and identify structural defects. This study [1] classifies defects found in the structures of saturated metallic composite castings. The proposed procedure for the detection and identification of structural defects of saturated metallic composite castings gravimetry, ultrasonic and X-ray, tomography, macroscopic tests, microscopic examination using light or scanning electron microscope, then its classification is carried out using the obtained image. The implementation of lightweight constructions based on composite materials requires the determination of the minimum damage size to still ensure safe conditions have to be identified and established in production as well as during the application, a review is presented in [2]. To assess the quality of welded joints, where one of the prospective flaw detections has a traditionally significant role, the magneto-optical eddy current (MOEC) method, in which surface, subsurface and fatigue defects can be recorded in products from both magnetic and nonmagnetic metals, as well as flaw detection of welds are considered in [3]. The measured impact duration can be used to obtain a "scan image" in various materials (especially honeycomb sandwich composites) [4]. The absence of visible defects along the route is an important condition for the safe movement of all modes of transport. Timely identification of defects and understanding of the operating conditions of materials and structures allow us to assess the time of their fault tolerance.

## 2. Goals and objectives of the work

Difficulties which are associated with a large amount of time for viewing by a person; expert experience; viewed images, fatigue occurs and possible loss of defects in the image arise at the stage of analysis of the obtained images. In addition, there is a high level of noise in the images in some types of diagnostics. Various methods are used to automate image analysis.

In this paper, we review the proposed solutions for detecting defects in various industries (Section 3) and propose a solution based on the convolutional neural network of the u-net architecture (Section 4), the efficiency of which is shown for various directions.

## 3. Detection and classification of defects

There are solutions to the problem of detecting defects related to various industry specifics. One of the universal approaches for image analysis is semantic segmentation, the peculiarity of which is that each pixel is assigned a certain label. The possibilities for implementing semantic segmentation have increased with the advent and spread of deep learning neural networks. The relevance of using this approach in flaw detection is confirmed by research.

The positive results of the use of convolutional neural networks (CNN) are illustrated for the segmentation of large materials imaging datasets obtained using x-ray computed tomography [5]; the structure of the fully convolutional network (FCN) provides identification of rock pore structures in scanning electron microscopy images to characterize the porosities [6]; generative adversarial network (GAN) model in a non-destructive testing system in thermography to detect defects in a carbon fiber reinforced polymer [7]; metallic defect detection [8]. In product manufacturing: technique of detecting defects in layers and improving the quality of small-scale products in additive manufacturing [9]. Solutions using CNN to detect surface defects: deep-learning-based small surface defect detection [10]; classification of defects on the surface of rails [11]; proposed deep FCN for classification of cracks on the surface of roads [12]; FCN for modeling the orientation of cracks in addition to their localization in order to identify areas requiring priority [13]; assessment of the integrity of bridge structures with the determination of the location of the cracks [14]; semantic segmentation of crack and leakage defects in a subway tunnel using feature hierarchies extracted by FCN [15]; to assess the severity of defects in sewer pipes [16]. An algorithm is proposed for detecting defects in self-shatterinng of insulator in the field of energy [17].

An analysis of the researches results showed the prevalence of the pointed out difficulties associated with the absence of a large set of data marked out by an expert (annotated training sample) and the need to detect small defects.

The possibility of using the u-net architecture [18] developed for biomedical image analysis is used in situations where there are few marked images. The possibility of its use in other areas is confirmed by successful experience for assessing the geological characteristics in images of shale samples obtained using a scanning electron microscope [19]; analysis of the microstructure of cement-based composites in microcomputer tomography images [20]; crack detection in tunnels [21] (features are small crack size and the presence of a high level of noise in the pictures; in the production of polycrystalline silicon wafers [22] (difficulties are associated with the heterogeneity of the background and unpredictable forms of defects).

## 4. Defining defects based on u-net architecture

U-net network was tested as a part of the search for the optimal solution to flaw detection tasks, including metal surfaces. One of the criteria for choosing this network for solving the real problem of flaw detection of welds of metal surfaces was a feature of a small number of training samples. Therefore, all selected datasets consist of a small number of tagged images. It was necessary to confirm the ability of the network to learn on a small amount of data. This is important because often the data is quite specific and the observed object or sign is rarely seen in photographs. The second important feature is the nature of the observed features. The network must reliably segment low-contrast objects that consist of only a few pixels.

The following were considered as test datasets: Magnetic-tile-defect-datasets (this is the datasets of the upcoming paper "Saliency of magnetic tile surface defects", https://github.com/abin24/Magnetic-tile-defect-datasets.), CrackForest Dataset (https://github.com/cuilimeng/CrackForest-dataset), Micro surface defect database (http://faculty.neu.edu.cn/me/songkc/Vision-based_SIS_Steel.html), Oil pollution defect database (http://faculty.neu.edu.cn/me/songkc/Vision-based_SIS_Steel.html). Another dataset is a dataset of images of welds of metal pipes with marked defects in the weld provided by a private company.

Padding was used in the layers during testing to preserve the dimension of the output of the neural network with its input. The size of all input and markup was reduced to a size of 256x256. For all datasets, the network trained during 100 epochs. There is a small part of the test results below (figures 1 – 4).
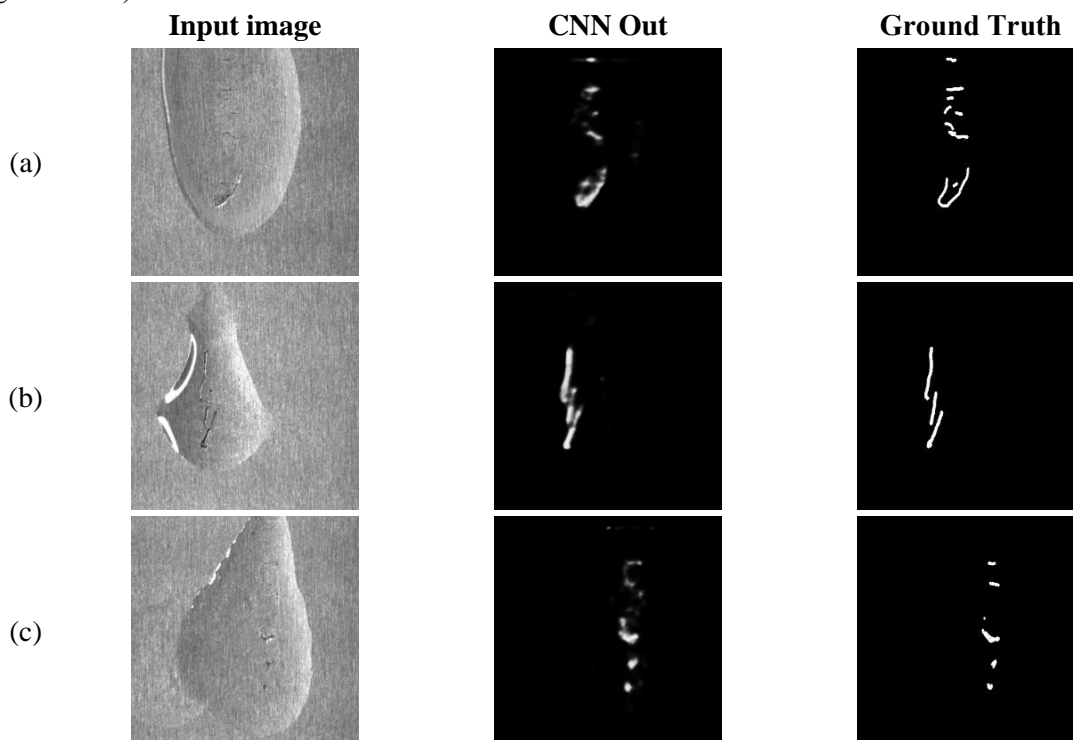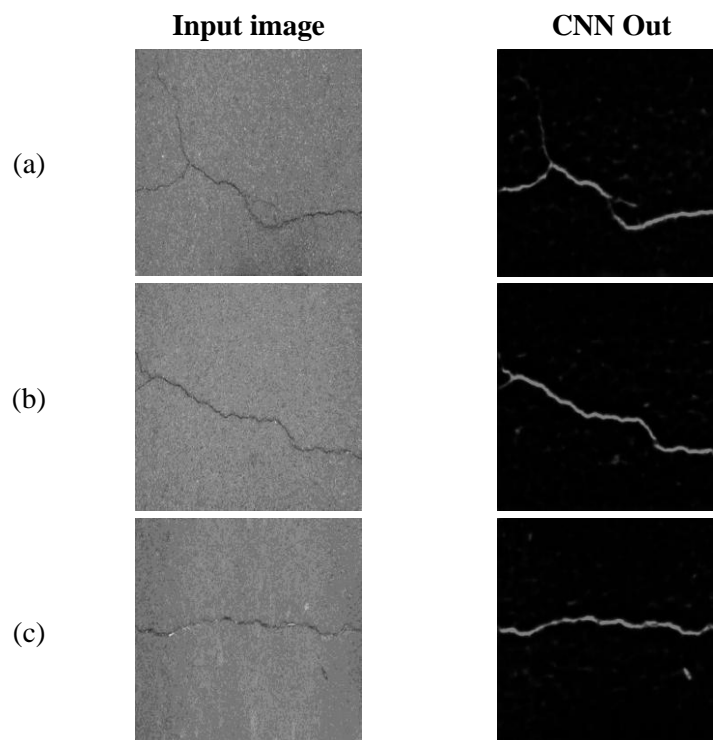


**Figure 1.** (a) – (c) Results on dataset Oil pollution defect database.
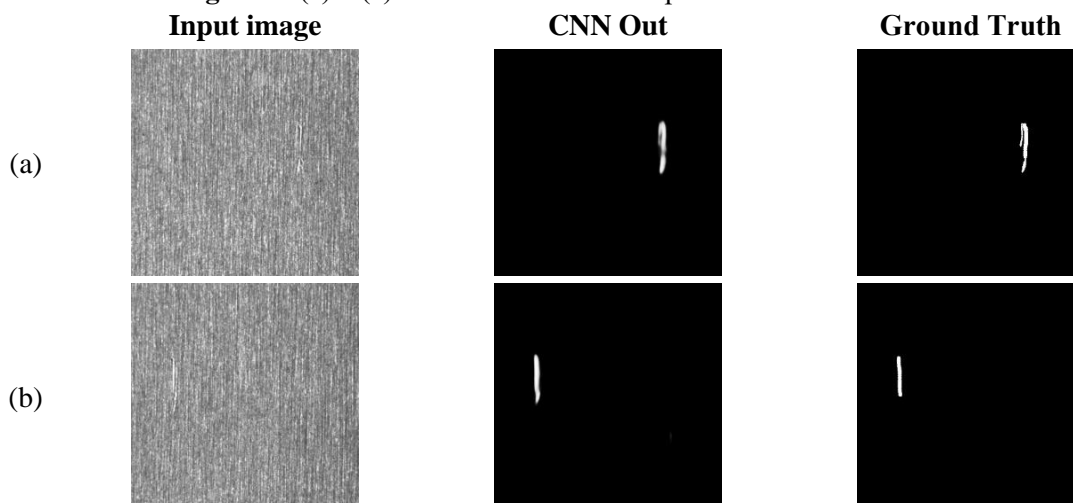


**Figure 2.** (a), (b) Results on dataset Micro surface defect database.

| Input image | CNN Out | Ground Truth |
| --- | --- | --- |

(a)

(b)
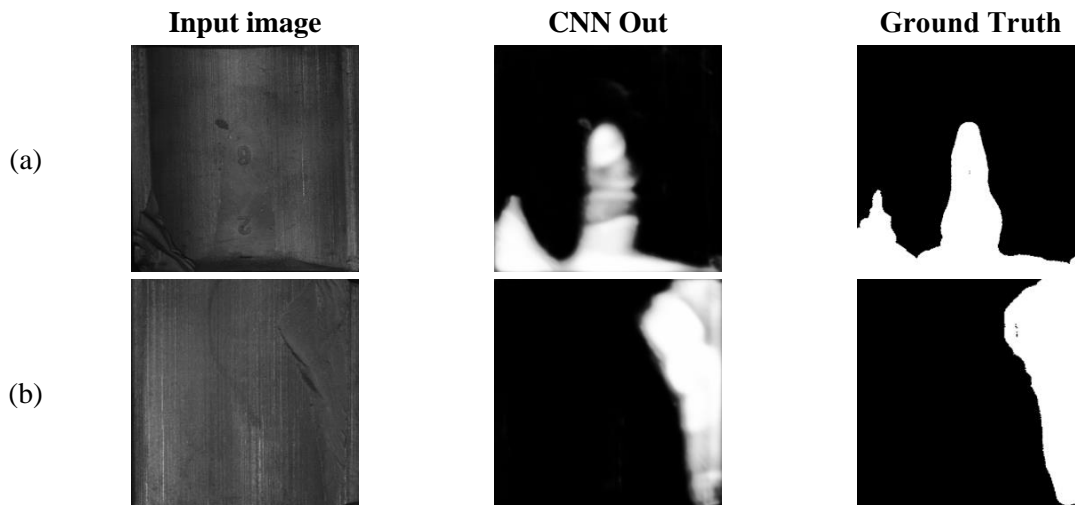


**Figure 3.** (a), (b) Results on dataset Magnetic-tile-defect-datasets.

| Input image | CNN Out |
| --- | --- |

(a)

(b)

(c)



**Figure 4.** (a) – (c) Results on dataset CrackForest Dataset.

The graphs of loss functions for u-net on the Microsurface defect database are shown in the diagram (see figure 5).

The results shown above demonstrate the effectiveness of u-net in recognizing defects on various surfaces. At the same time, defects are often of low contrast and have an arbitrary shape. The use of a dataset with road damage here is due to some similarity of cracks in the asphalt with possible cracks in metal surfaces. In addition, testing of the classification of defects in welds was conducted. In this case, pores and slag inclusions were classified on the X-ray of the weld Despite the close visual similarity (close visual features) of these defects, u-net reliably detected and classified these defects.
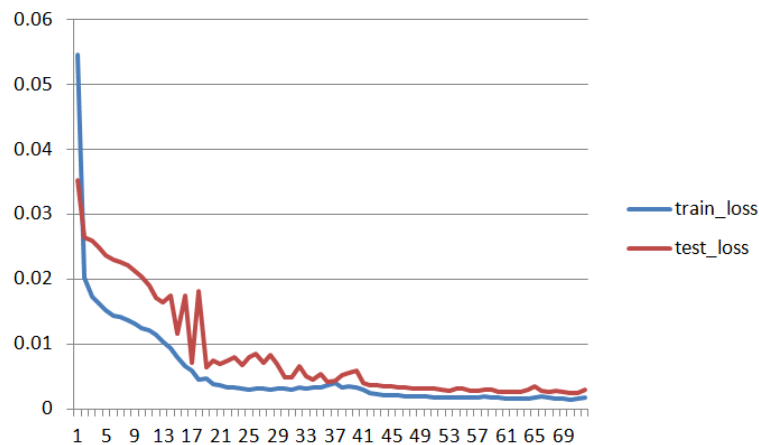
**Figure 5.** The graphs of loss functions for u-net on the Micro surface defect database.

## 5. Conclusion

A review of recent studies in the field of flaw detection showed positive results using semantic segmentation based on convolutional neural networks in a wide range of industry tasks The u-net architecture network was selected and successfully tested, taking into account the identified features in the formulation and implementation of the problems of detection and classification of defects. The directions of further research will be related to the definition of specific settings for industry decisions in order to use it as a key element of the decision support system.

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