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APPLICATION OF THE ALGORITHM GOOGLeNeT FOR QUALITY CONTROL USING COMPUTER VISION

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Industry 4.0 is characterized by increased flexibility in production along with a wider individual approach to the product, better quality and increased productivity. With the wide implementation of "smart" sensors and optical cameras, the need to process large arrays of data recorded during the production process and informative from the point of view of research and product quality assurance has also increased. This leads to the application of deep machine learning, which plays a decisive role in the processing and analysis of information about the product, etc. In recent years, algorithms and programs based on deep machine learning have achieved significant progress in their application in the industrial sphere, this effectively contributed to the development of intelligent production and accelerated the emergence of Industry 4.0 [1].

Figure 1 shows the machine vision-based approach to checking phragmites tube defects, which was considered in the paper. It includes the following steps: raw image acquisition, surface sampling, roller ring region expansion, small dataset preprocessing, machine learning model training, and feature classification [2].

Fig. 1. Defective Phragmites tube

The computer vision system collects images using a monocular camera and a tuned system of light sources. The algorithm contains 386 raw images that improve the reliability of the classifier, these images cover different lighting conditions by adjusting the brightness of the lighting system.

To improve the operation of the output control algorithm, the tubular image of the research object is transformed into a rectangle using polar-Cartesian transformation (P2C) we denote the coordinates (C_x , C_y) the center of the tube; (R і R_0) denote as outer and inner radii, respectively; (P_x , P_y) and (D_w , D_r) represent the coordinates of the corresponding points to and after conversion respectively. The P2C transformation can then be described as:

$$\begin{cases} x = C_x + (r + p_0) * cos(\theta) \\ P = C_p - (r + p_0) * sin(\theta) \end{cases}$$

where $\theta = 2\pi w/W$

To ensure the quality of the resulting image, the bilinear interpolation method is used to obtain the correct pixel value [1].

The machine learning system recognizes defects according to the following criteria: pigmentation, film presence, diameter deviation, length deviation, end cracks, internal cracks, scratches, stains, fractures and shape deviation. According to the defect, it keeps statistics of the number of objects under investigation and automatically sorts them into specific classifiers.

Data processing proceeds as follows: first, the label expansion method is used to solve sample imbalance problems. The SSAD method is then used to optimize the input data. The resulting data is automatically divided into three parts: training set, validation set, and test set in a ratio of 3:1:1.

Sample training is performed using four state-of-the-art machine learning architectures, SqueezeNet v1.1, Inception v3, VGG-16, and ResNet-18. The trained model is then used to classify the phragmites tube image through a sliding window to obtain the final validation result [3-4].

But the above actions are still not enough to eliminate the overall imbalance of output control and deep learning of the network. Therefore, it is necessary to artificially improve the received data. The general principle of enhancement is to randomly crop, scale, rotate, return and add random noise. The defect that occurs on phragmites tubes is an end crack that appears after the cutting operation, but such a defect is recognized as insignificant, and the position is not fixed, the function of the study is unlikely to include the fault (Fig. 2).

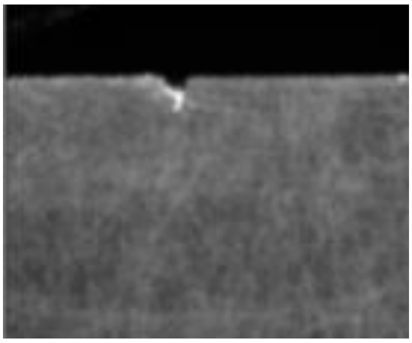

Fig. 2. End crack

In recent years, much of the research in computer vision scanning has focused on increased accuracy. By training the GoogLeNet network algorithm with an extended data set, attention is paid to the end parts of the research object. A map of the intensity of correspondence at the extreme boundaries of the object sweep is compared (Fig. 3). An image of a single tube in multiple locations, randomly scaled, and viewed in detail.

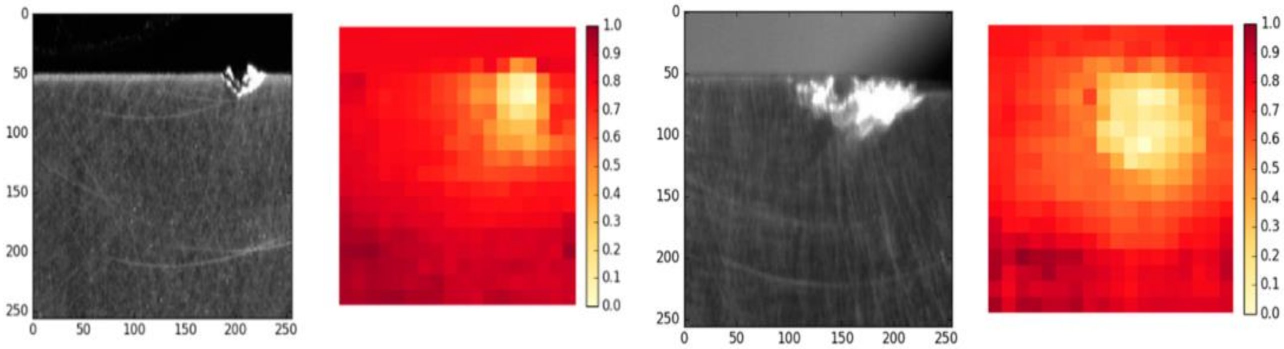

Fig. 3. The end crack is processed by the GoogLeNet algorithm

As a result of achieving previously unattainable cracks, chips and slots on the ends, which were previously recognized as the outline of the product. By looking at the original image, but in an edited format, the level of quality control is greatly achieved without significantly increasing the amount of data that can be processed without being loaded on this computing machine.

The paper considered an approach to inspect phragmites tube defects based on machine vision through deep learning. The GoogLeNet algorithm was considered, which made it possible to eliminate defects of small end cracks on phragmites tubes. From the perspective of further research, it is planned to work on the optimization of the initial quality control system using computer vision.

Keywords: computer vision, methods, automated production, quality control.

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