Ministry of Education and Science of Ukraine

Odessa National Academy of Food Technologies

International Competition of Student Scientific Works

BLACK SEA SCIENCE 2021

Information Technology, Automation and Robotics

Proceedings

Odessa, ONAFT 2021

UDC 004.01/08

Black Sea Science 2021: Proceedings of the International Competition of Student Scientific Works. Information Technology, Automation and Robotics. / Odessa National Academy of Food Technologies; B.Yegorov, M. Mardar, S.Kotlyk (editors-in-chief.) [*et al.*]. – Odessa: ONAFT, 2021. – 526 p.

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Odessa National Academy of Food Technologies, 2021

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SYSTEM OF AUTOMATED DETECTION OF CERAMIC DISC SURFACE DEFECTS

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Abstract. *A handheld USB digital microscope is considered as an instrument for ceramic disk inspection automatization in the production cycle. It provides the opportunity for surface defect detection in the needed range from 50 to 500 μm. Such a device providing 15 fps with the standard VGA resolution of 640x480 pixels enables one track scan for 18 seconds. As a decision unit, a system based on the artificial neural network was used. The basic system software has been developed. A study of the object illumination and the size of the database influence on artificial neural network training results (probability of defect detection) have been carried out. The use of digital filtration, adaptive histogram equalization, threshold function, and feature detection as a classical approach showed a good result. Deep learning has proven its effectiveness, selecting features of the defect and presenting more stable results in defect detection.*

Keywords: *artificial neural network, image recognition system, digital microscope, ceramic discs.*

I. INTRODUCTION

Technical ceramic parts have increased use in textile machinery. For example, ceramic discs used for texturing yarns as guide discs, working discs, and knife discs. Ceramic components offer significant performance enhancement in textile machinery due to optimized grip and eliminated snow, as a result of special surface engineered features.

The studied ceramic disks Rapaltex [1] (Fig. 1) are used in the equipment of thread weaving of the textile industry.

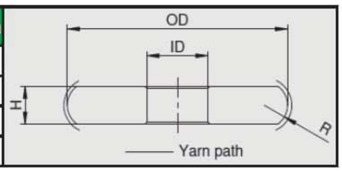
Fig. 1. General expected discs view

Special fibers are intertwined with each other on a certain trajectory, which is set by their passage through the cassette with a certain location of such disks. Contact from disks with fibers occurs on working surfaces. The nominal disk parameters [1] are as follows (Table 1).

Table 1. Disk nominal parameters

Working Discs - STANDARD

Article-No.	OD	ID	H	R	Shape	Surface Ra
90747-1	52	14,45	9	5,5	C	0,85
90750-1	52	12	9	5,5	C	0,85
90749-1	49,62	12	6	3,5	C	0,85
90748-1	45	12	6	3,5	C	0,85



The presence of defects on these surfaces leads to damage to the fibers and rupture of the thread, which is unacceptable. As examples (Fig.2) are shown images of typical defects taken with the help of a digital microscope Qscope QS.20200-P [2].

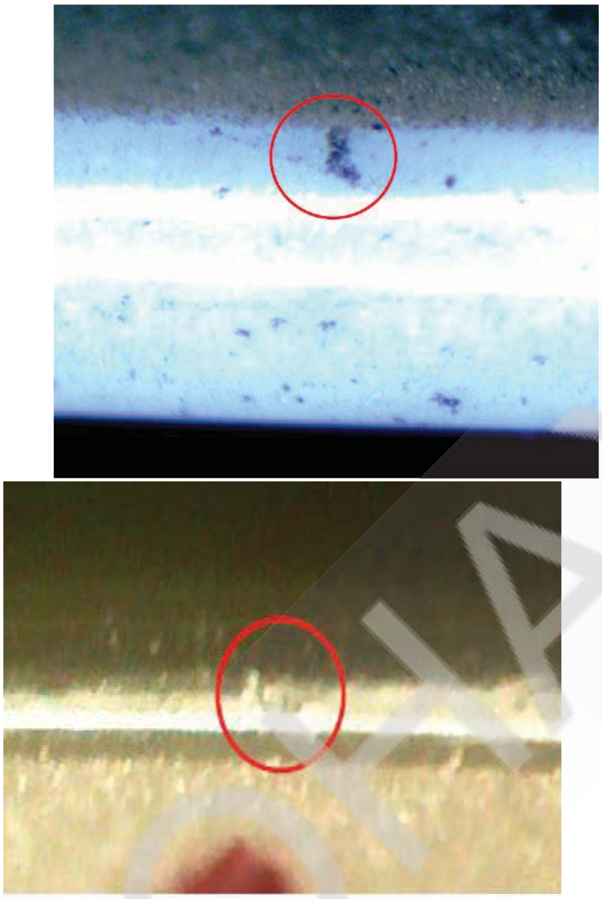


Fig. 2. Typical disk defect examples

There were also some pictures available from manufacturer (Fig. 3).

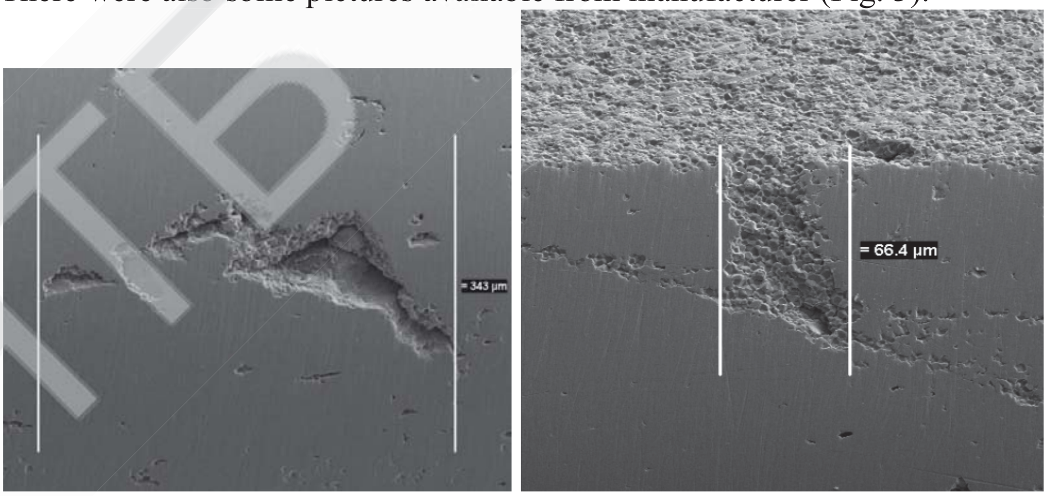
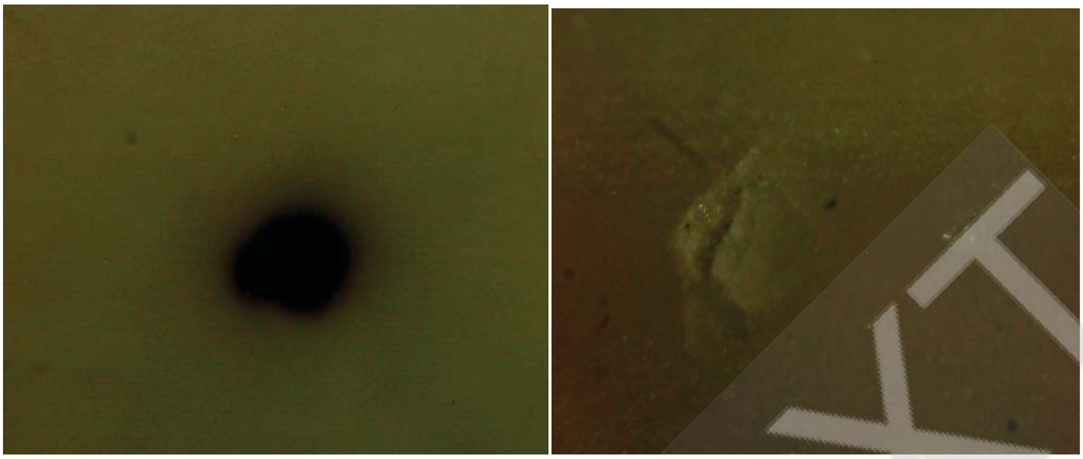


Fig. 3. Disk defect examples

Preferably, these are crater-like depressions with a surface area of 50 µm or more, but there may be chips, scratches and dark spots, which are also defects (Fig. 4, a - b).



a/ b/

Fig. 4. Typical disk defect examples

The depth of these defects can vary, preferably up to 0.5 mm maximum, but there are cases of defects that are not actually deep, which creates obstacles to their identification by classical sensors scanning the surface of the object.

The working surface of the disk is checked for defects. As you can see, this is the edge of the disk with the radius set for each type of rounding radius. This part of the rotating disk is in contact with the thread. Defects described above damage the thread, it leads to its rupture, as a consequence - lack of production, damage.

The problem is that nowadays surface quality check of such parts is performed visually by highly qualified personnel with extensive experience. The reason for this is the complexity of the inspection and therefore difficulty to automate the quality control of ceramic products.

II. LITERATURE ANALYSIS

Areas with defects were studied using a digital microscope Qscope QS.20200-P [2]. It was found that the defects are up to 100 μm in size as well as the possible methods of ceramic disks defects detection are analyzed. For inspection of ceramic surface different types of instruments can be used: ultrasonic sensors [3], laser profile scanners [4], microscopes with image processing algorithms [5]. It was defined that inspection equipment hardware should provide the necessary resolution and defect detection ability and at the same time, it should be cheap and easily accessible. The problem is that ultrasonic instruments are designed for an in-deep view of the material, and our object of interest is located on the surface. The existing laser profile scanners [6] are relatively costly and can not fully solve the problem, because certain defects can be identified only visually. Laser scanners do not allow to identify all the necessary types of defects, which will lead to product shortages, and secondly have a very high price, which makes it impossible to conduct even the experimental part. However, with the development of technology, more and more tasks of automation, even such complexity can be solved. Against this background, we continued to work with the available USB digital microscope. It was decided that it will be economically feasible to use a digital microscope from Qscope that does not lose in accuracy, and the system is much cheaper than commercially available scanners.

The next question was which algorithms can be used. Classical edge detection methods from the image processing toolbox are problematic to adapt to a wide range of defect shapes. The choice of a defect detection system using a digital microscope and an artificial neural network [7-9] was substantiated. There is one of the top and free image processing library [10]. It enables us to build systems with self-contained Deep Learning and Computer Vision capabilities using simple code. As an analogue, the Python image object recognition system, in particular based on the ImageAI library, was chosen for the study. To work with ImageAI, you need to install Python 3.6.-version, as well as some other libraries and Python frameworks. ImageAI provides very powerful yet easy-to-use classes and functions for detecting image objects, allowing you to perform all these actions using state-of-the-art deep learning algorithms such as, and. With ImageAI, you can run detection tasks and analyze images. Such a system has advantages in the relative simplicity of design, price, and ease of operation.

III. OBJECT, SUBJECT, AND METHODS OF RESEARCH

The ***object of the study*** is image recognition with a deep neural network system for detecting defects in the images of ceramic discs.

The ***subject of the study*** is the ability of the system to detect defects and its sensitivity to external factors.

The aim of this work is to provide reliable detection of ceramic disks defects using a low-cost system, based on a digital USB - microscope. The system should perform a visual inspection of surface quality.

The training of the artificial neural network is carried out on the same type of photographs, containing and accordingly marked defects of different types and nature. In such conditions, as for the requirement of more correct operation of the network, after its training, for research, it would be necessary to give photos of the object with approximately the same lighting as in the photos on which the network was trained. There were used in the work 300 photos (although about 5000 photos are recommended for the correct operation of the network) owing to the limited defect examples number at hand. They were divided into two parts for training and test folders as 80% / 20%, i.e., 264 photos for neural network teaching, and 66 photos – for testing. The basic software of the system was developed. It was enough to defect detection with the probality more then 90%. It is experimentally established that if the probability of finding a defect is lower than 70%, the system begins to work incorrectly. That is, it finds objects - defects that are not really defects, or does not detect real defects. A study of the influence of object illumination change factor during system operation and the size of the database for training an artificial neural network on the probability of defect finding was performed.

Usually, the neural network is trained to find typical objects that have clear common external features (cars, people, specific objects, etc.), here the image is the same type (always the same background), when the image appears strange object, the system must identify it as a defect. Therefore, the training of an artificial neural network is carried out on the same type of images containing and accordingly marked defects of different types and nature. In such conditions, in order for the network to work as correctly as possible, after its training, for research, it would be necessary to take photos of the object with nearly the same lighting as in the photos on which the network was trained.

IV. RESULTS

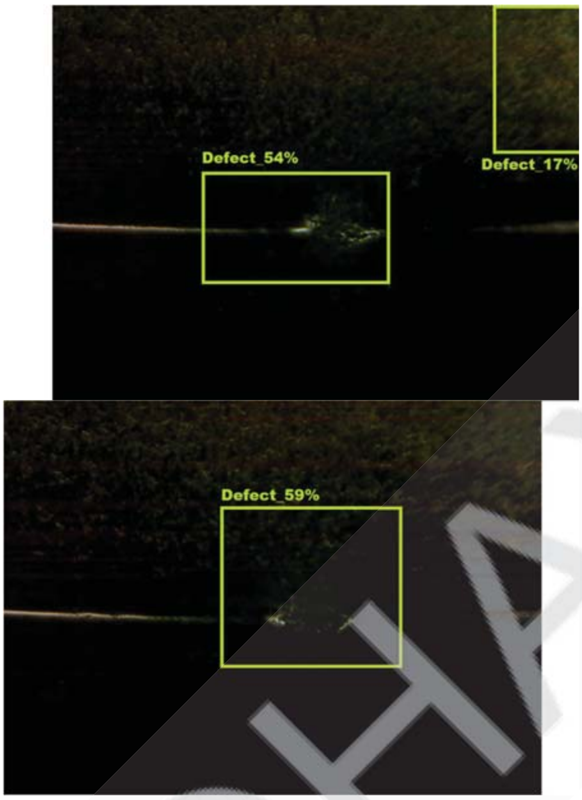
2.1. Object illumination influence experiment

Thus, when the system works (search for a defect in a photograph) with photographs in which the illumination of the object is the same as in the training photographs, were obtained the following results (examples in Fig. 4).

a/ b/

Fig. 4. Disk defect discovering examples

To study the effect of lighting influence a series of twenty shots with same lighting level was taken for four known defects. The graph of the result is given below (fig. 7 - "blue line"). It can be seen that the probability that the found object is checked as defect ranges from 94% ± 5%. Because the surface of objects is almost uniform in terms of the reflection coefficient, the image histogram (graph of statistical distribution of brightness values for image pixels) is relatively narrow (30-40% of the range of values) and remains approximately the same at different intensity values. Therefore, it was decided to determine the light intensity by the peak of the image histogram. Now, let's take photos of these same defects in the worst light and check them by our created system (fig. 5).

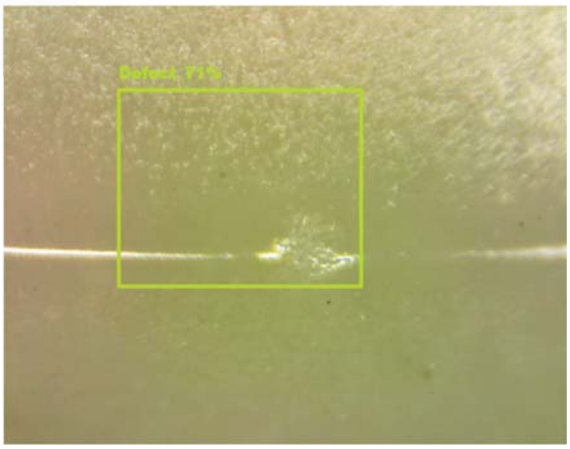


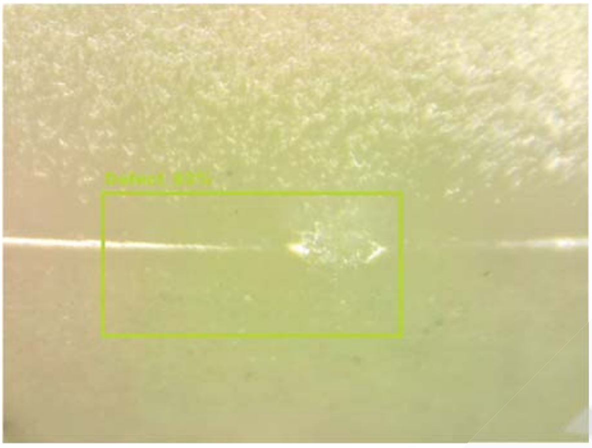
a/ b/

Fig. 5. Disk defect discovering in the worst light examples

For reliable statistics, there was checked the result also on 20 photos, the graph of the result is given below (fig. 7 - "red line graph"). As you can see, the probability that the found object is checked as defect ranges from 55% ± 10%. Experience has shown that a result with a probability of less than 70% is unacceptable, because in most cases the object is not a defect. So, the system started to work incorrectly. Therefore, such a change in lighting is not permissible.

Now, let's take a photo of these same defects in the brighter light and check them by the system (fig.6).





a/ b/

Fig. 6. Disk defect discovering in the brighter light examples

For reliable statistics, check the result on 20 photos, the graph of the result is given below (fig. 7 - "grey line graph"). The following results were obtained - the average probability that the object found is a defect range from 35% ± 10%. In some cases, the system either did not find as defect at all or gave a false result. It is obtained the clear conclusion: such a change of lighting is extremely unacceptable!

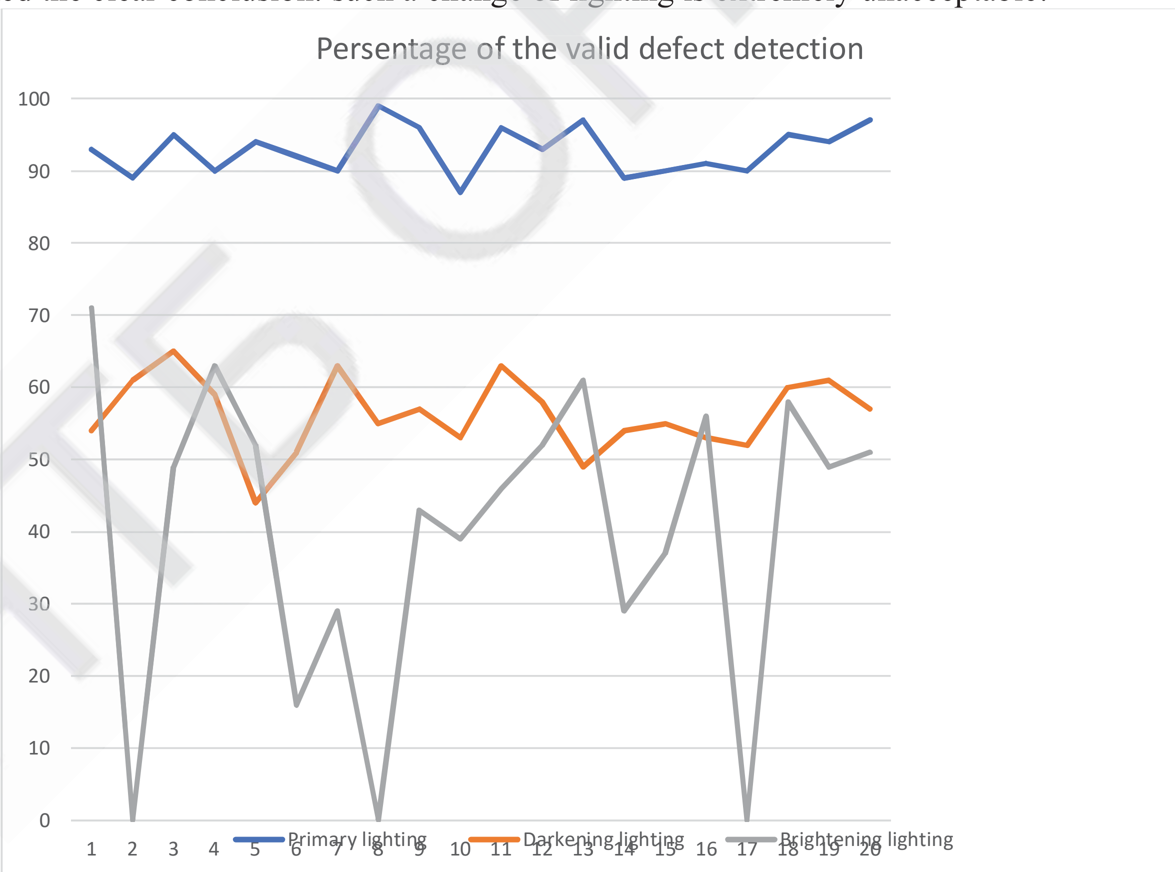


Fig. 7. Experimental results of defect detecting probability vs the experiment number for different lighting conditions

It has been experimentally established that the optimal results (the best image contrast) are achieved at the histogram peak in the range of 25% - 35% of the intensity range. With decreasing intensity (approaching the histogram peak to 10%), the probability of detection decreases to 70%. With the subsequent decrease of the peak of intensity (up to 5%) the probability decreases to (20 - 50)%, which is unacceptable. A similar pattern is observed with increasing intensity, ie the shift of the histogram peak in the range of more than 50%. The probability of detecting a defect in this case also falls below 70%.

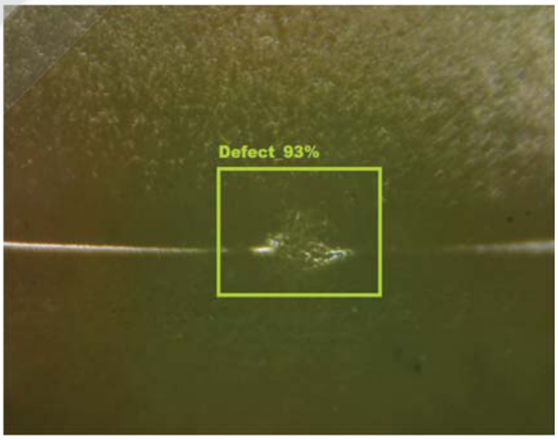
2.2. Training image number influence

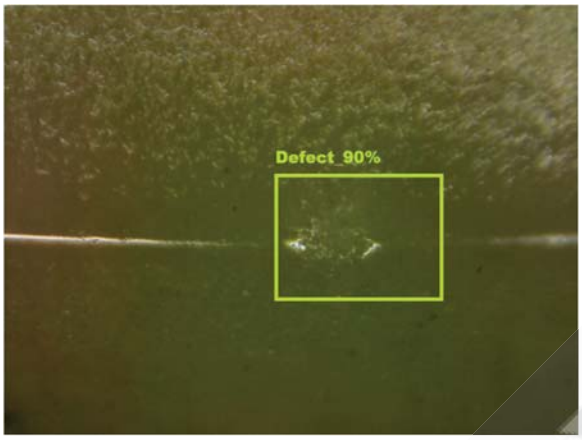
The accuracy and correctness of the artificial neural network depends on many factors. The most important stage of creating such a system for a specific task is the stage of training an artificial neural network. During the training of an artificial neural network, several factors are considered, one of the most important is the training database. In our case, this is a certain number of photos with defects. According to advanced neural network developers, the systems used in object recognition in the image require a recommended minimum number of training images in the amount of 5,000 images (files). It was recognized how this factor affect the operation of the system. Similar to the previous study, there were conducted three experiments.

For the first experiment it was used the initial data from the previous study, namely: for a minimal demonstration of the system, 100 photographs and 2,000 training cycles of an artificial neural network were used in the training of the network.

It was kept the number of training cycles and other parameters unchanged but was changed the number of photos to larger and smaller sides, respectively. So, let's move on to the first experiment.

As was mentioned above the number of photos for training was equal to 100 examples. Training cycles of artificial neural network was equal to 2000. The results can be observed below (Fig.8).





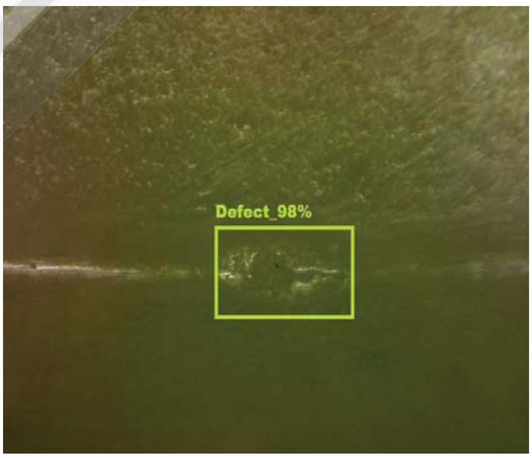
a/ b/

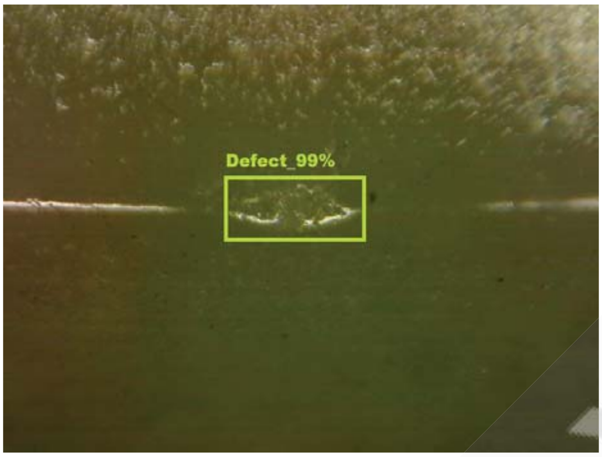
Fig. 8. Disk defect discovering examples with 100 samples

To create statistics, check the result on 20 photos, the resulting "blue line graph" is given below (fig. 11). As you can see, the result is satisfactory, the system works correctly, the probability that the found object is a defect is higher than 85%, which is an excellent indicator.

Now let's increase our training database from 100 to 200 photos. After training and checking the system, the following results were obtained (Fig. 9).

To create statistics, check the result on 20 photos, the "red line graph" of the result is given below (Fig.11). As you can see, the result is satisfactory, the system works correctly, the probability that the found object is a defect is higher than 85%, which is an excellent indicator. Comparing this result with the previous one, we can see that the system has become more accurate, the percentage of the found object is a defect has increased to an average of 97%, the highlighted area of the defect has become more accurately positioned. Therefore, we can conclude that the increase in the training database is a positive indicator for improving the accuracy and correctness of the system.





a/ b/

Fig. 9. Disk defect discovering examples with 200 samples

Also was conducted the third experiment, reducing the training database from 100 to 50 photos. The following results were obtained (Fig. 10)

a/ b/

Fig. 10. Disk defect discovering examples with 50 samples

To create statistics, check the result on 20 photos, the "grey line graph" of the result is given below (Fig. 11). It can be seen that the result is unsatisfactory, the system sometimes does not work properly, the probability that the found object is a defect is less than 85%, which is an unacceptable indicator. Comparing this result with the first and previous, we can see that the system has become less accurate, the percentage of the found object is a defect decreased to an average of 67%, the highlighted defect area became less accurately positioned, false signals appear. Thus, it may be concluded that the reduction of the training database is a negative indicator for the accuracy and correctness of the system.

Down (Fig. 11) is put a common graph to demonstrate the results of the experiments. Thus, it noticed that increasing the size of the training database increases the accuracy and correctness of this system and reducing on contrary - lowers and leads to unsatisfactory results.

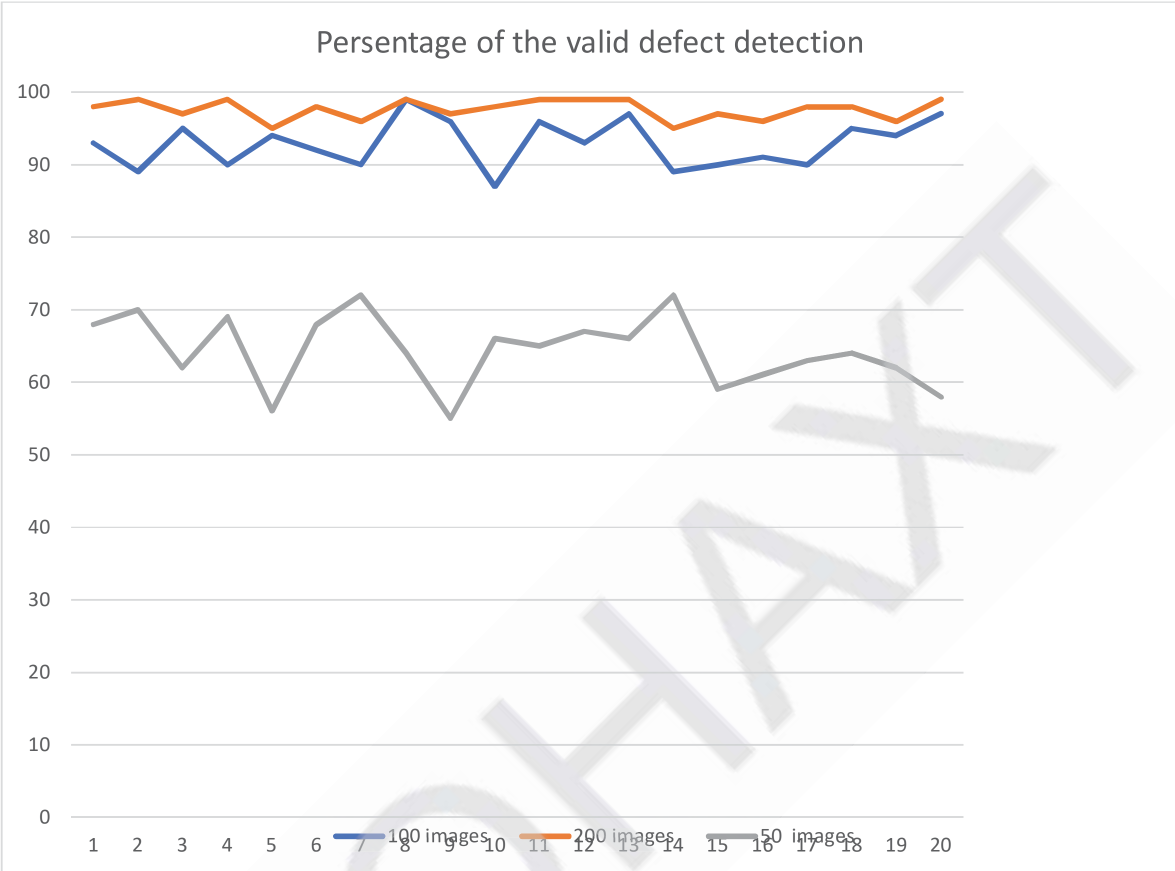


Fig. 11. Experimental results of defect detecting vs the experiment number for the different training samples number

V. CONCLUSIONS

Possible methods of detecting defects of ceramic disks were analyzed and it was decided that it is economically feasible to use a digital microscope from Qscope that responds to the requirements of accuracy, and the system hardware is much cheaper than the scanners available on the market.

The areas with defects were investigated using the handheld USB digital microscope Qscope QS 20200-P. It was experimentally found that the defects have sizes up to 100 μm with the different shape and size of the defects.

The choice of a defect detection system using a USB digital microscope and an artificial neural network was substantiated. Such a system has advantages in the relative simplicity of design, price, and ease of operation.

Features of use of the chosen software were developed, as well as specifics of the training process of an artificial neural network. Also, there was investigated the system operation at the different object illumination levels, and the different number of images for training. The practical implementation of the system has proven its functionality and efficiency, so it can be concluded that the main purpose of this work has been achieved.

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