Intelligent Machine Vision Implementation for Production Quality Control

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Abstract—**The paper presents a quality guarantor solution for modern production enterprises based on the combined use of artificial neural networks within a distributed machine vision platform. The platform includes a set of hardware and software modules for visual technical quality control of production processes. There are presented two typical modules for visual inspection of product external appearance and internal parts, spaces and openings using an endoscope video camera. Digital platform software is built for semantic and statistical processing of Big Data characterizing the state of the technological process. The results of the solution implementation in practice are illustrated by several cases of automated visual control of products, automatic verification of the presence of structural fasteners, automated sorting of products, and inspection of internal surfaces and recognizing of holes. Implementation of quality guarantor architecture and design technique based on covering the production process with the modules of external and internal visual quality control allows improving the quality indicators due to systematic and targeted application of intelligent machine vision.**

I. Introduction

Intelligent machine vision technologies allow quite successfully solving the problems of quality control in machine-building production. However, their implementation in practice is seriously limited by the field of visual detection of defects and faults. In this sense, machine vision technologies lose to instrumental control tools, primarily in terms of accuracy and reliability.

At the same time, at the scale of the production line, the introduction of machine vision allows for a wider coverage, implementation of bottleneck control and monitoring of both quality of products and correct execution of the technological process and individual production operations. This approach makes it possible to build more universal and cheaper quality management systems, which is in demand at many modern machine-building enterprises. Easier tuning of machine vision systems due to retraining of neural networks allows you to quickly adapt existing quality control tools in the event of a production upgrade and a change in the product range.

This paper proposes a new approach to the implementation of a quality management system based on the combined use of artificial neural networks within a distributed machine vision platform called "quality guarantor". Below are the features of the implementation of this approach and recommendations for its application in practice.

II. State of the Art

Nowadays industrial automation provides extensive use of machine vision technologies for manufacturing quality control [1]. It develops according to the trends of Industry 4.0 [2, 3] and integrates technology stack of imaging using video and photo cameras or specific sensors, image processing and automated decision-making, including with the involvement of artificial intelligence and deep learning [4].

The main purpose of machine vision is to automatically extract the required information from initial data represented by images or video. In production enterprises machine vision is used for imaging-based automatic inspection, process control, inspection and sorting etc. [5].

Based on the features of the application of machine vision, its use mainly concerns the identification of visually observed objects, events or phenomena [6, 7]. In this regard, in production, machine vision is used in visual quality control systems [8, 9], where it is implemented by an automated integrated complex of cameras, sensors, software and robot guidance. It should be additionally noted that some approaches can be borrowed into production from other industries, where computer vision shows significant results in identifying deviations from quality standards [10, 11].

In industrial computer vision systems, the leading role is given to automatic diagnostics or decision-making support modules. Artificial neural networks are actively used here, since they provide high adaptability and customization and allow eliminating the influence of the human factor [12, 13].

For example, artificial neural networks are implemented in computer vision quality control in an enterprise that employs people with visual impairment [14]. In this case, the effectiveness of the use of machine vision is ensured by the need to compensate for the human disability and provide greater adaptability of workplaces.

In addition to the detection of defects and production quality control, neural networks provide machine vision solutions with the possibility of processes monitoring and prediction of quality risks and issues [15]. Quality diagnostics based on learning technologies provide higher adaptability and possibility to predict divergence of product physical parameters from an acceptable range of values [16].

Practical implementation of an intelligent computer vision system requires a specific solution considering the features of an automated production enterprise [17, 18]. In this case they are capable of achieving significant results [19].

Despite the universality of artificial neural networks, there is no single solution for the implementation of an intelligent visual quality control system. However, the development of special solutions for each individual case requires large financial and time costs. In this regard, a methodology is needed to build a quality control system based on a common digital platform for intelligent computer vision.

In this paper we propose a new approach to solve this problem based on the concept of a quality guarantor [20]. There are presented some software and hardware solutions implementing artificial intelligence and the results of their practical application.

III. Quality Guarantor Approach

Quality guarantor is a new architectural and technological solution for a machine vision digital platform implementing artificial intelligence. The platform includes a set of hardware and software modules for visual technical quality control of production processes. Digital platform software is built for semantic and statistical processing of Big Data characterizing the state of the technological process.

Being integrated into an enterprise information space, the quality guarantor allows you to collect data for each individual workplace or production site and transfer them to an integrated monitoring platform as part of a situational production control center. The versatility of the applied models makes it possible to use the quality guarantor to monitor the quality of mechanical processing of products and identify visually observable defects, as well as to control the correctness of manual and robotic operations performed by personnel.

Image recognition is provided using artificial neural networks, trained using video recordings of suitable parts, defects, correctly performed technological operations and possible deviations, including deviant behavior caused by the influence of the human factor. This approach increases the versatility of the application of the quality guarantor modules in production and allows it to be used to solve a wide range of technical control tasks.

Quality guarantor architecture and design technique are presented in Fig. 1. This technique can be used as guidelines for analyzing and improving the quality management system of an enterprise and contains the main stages of such analysis. The main task is to arrange technical control modules based on machine vision to increase the accuracy and reliability of the calculation of quality indicators, as shown in the center of the figure. On the right there is presented a list of steps in the methodology.

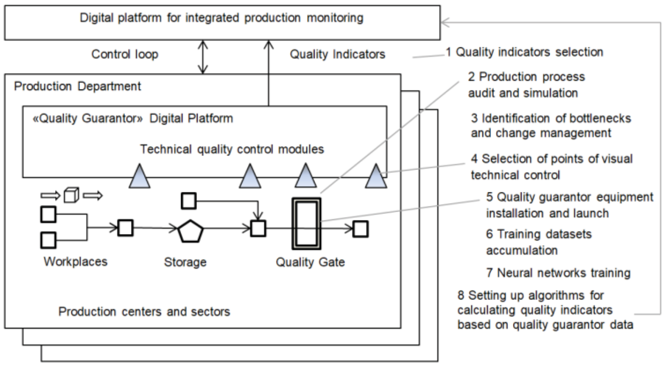

Fig. 1. Quality guarantor architecture and design technique

Based on a comparison of a set of target quality indicators and the current state of the production process, the system identifies bottlenecks and the most suitable points for introducing technical control modules. Such an approach provides rational coverage of production lines by quality control facilities, considering the possibilities and limitations of visual technical control.

Under the conditions of direct application of the modules, the training data is accumulated for the neural network image processing algorithms. Training is performed using statistical data and the results of video filming of production operations performed by highly professionals. If it is difficult to specify defective samples, three-dimensional modeling of defects with high realism is performed and the training set is supplemented with simulation results.

For most applications we have selected a convolutional neural network with YOLO architecture version 4. Such a solution was justified by its reliability and availability of integration into the application. The trained weights of YOLO v4 are relatively easy to transfer to the C# programming language, which is beneficial for increased performance and use on a system primarily written in C#.

The transition to later YOLO versions (7 and 8) was not carried out due to the rather large labor costs with little effect. YOLO v7 uses the framework Pytorch, which makes integration into other languages difficult. The difference in prediction accuracy is about 3% [21], which is not so significant compared to the much increasing complexity of integration into application.

The results of quality control are transferred to a digital platform for integrated production monitoring, which is the basis for business analysis and situational quality management. Therefore, the quality guarantor approach makes it possible to implement intelligent decision support not only in workplaces and production sites, but also at the level of management of a manufacturing enterprise in general.

Currently, the described solution is being tested at a number of manufacturing enterprises in the automotive and aircraft industries and is acquiring a high potential for practical use.

IV. Design Solutions

According to the introduced approach there was developed a set of hardware and software modules for visual technical quality control. The development took into account the requirement for the organization of control in streaming mode for the compliance of the parameters of parts with the quality parameters from the technological documentation.

The first module provides the visual inspection of product external appearance (see Fig. 2).

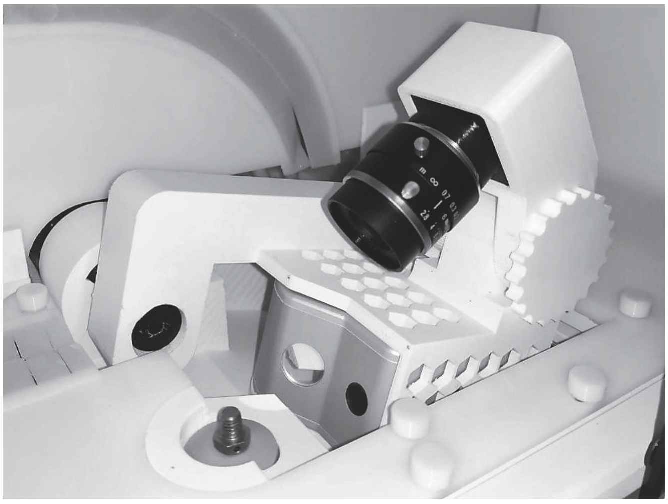

Fig. 2. Visual control module for product external appearance inspection

The functioning of the modules is based on measuring the geometric parameters of the product using RIFTEK laser sensors and calculating the control parameters using mathematical algorithms. Inspected object is located on a turntable, and a laser scanner is mounted on a swivel arm. Visual parameters are tracked by a neural network based on photo/video data.

To implement the rotation of the laser around the plane, a rotary mechanism for lifting the laser to a vertical position was developed. The turntable and the laser scanner are positioned relative to each other in such a way that the scanned object is always in the scanning area. The proposed general concept of the kinematics of the laser and the table provides the alignment of the axis of rotation of the arm and the working area of the laser.

Module deployment includes the following steps:

- Calibration;
- Placing the inspected object on the turntable;
- Rotating of turntable around its axis by 360 degrees;
- Rotating of the laser and camera by 90 degrees, at which time the turntable makes another turn.

To build a 3D point cloud using a 2D laser scanner Riftek RF627, each 2D profile obtained as a result of scanning and representing an array of points on a plane is being converted into a three-dimensional array of coordinates, oriented in the correct way in three-dimensional space, and then combined into a single 3D array of coordinates.

Such an approach provides automatic inspection of the object from all sides, which allows you to ensure the highest accuracy and consistency of measurements. Swivel design, laser sensor, HD camera, turntable, drives are placed in a metal case, complete with personal computer. The device turned out to be compact, autonomous and ergonomic (height 0.6 m; width 0.4 m; length 0.4 m).

The second module provides the visual inspection of internal parts, spaces and openings using an endoscope video camera (see Fig. 3).

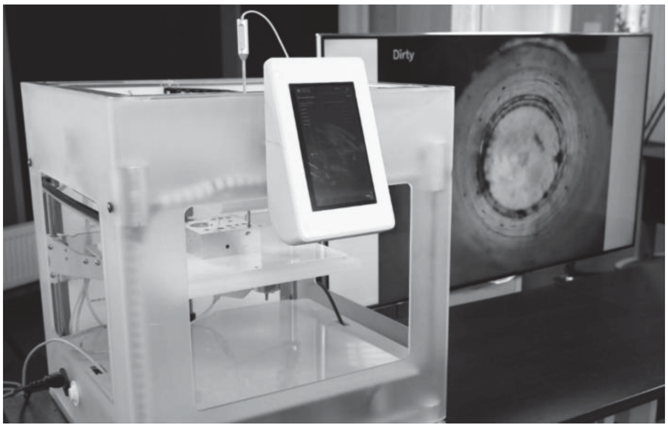

Fig. 3. Visual control module for product internal inspection based on a visual camera-endoscope

The hardware part of the module is built on a 5-axis machine, the working area of which allows access to all surfaces of the controlled part, except for the base. The approach to the base of the part will be provided by turning it over manually. Accurate positioning of the part on the machine's coordinate table and its correct turning by the user will be ensured by specialized equipment that makes it impossible to incorrectly position the part, as well as by using a neural network that recognizes the correct position of the part before starting to control a specific list of holes.

The module uses jProbe GE Gun Expert video endoscope. The endoscope is designed to inspect internal openings and is equipped with a manual mechanism for adjusting the focal length, implemented by moving the side-view mirror adapter, which allows high-quality inspection of holes of various diameters. The optimal focal length can be adjusted depending on the diameter of the inspected hole, which allows you to get the most clear image. The scanning procedure is based on recording of the coordinates of points of two-dimensional profiles reflected from the surface of an object rotating on a turntable into a binary file.

Below we describe software solutions for collecting and processing data within the framework of the operation of these typical modules.

V. Scanning Algorithms

Algorithms for working with a laser scanner and processing the resulting point clouds were built by an iterative method, each subsequent version of the algorithm took into account the pros and cons of previous attempts. Further, the results of each stage of testing the algorithm, the identified problems and proposals for their solution, as well as the final version, are presented.

A. Main Algorithm for Building 3D Models

The first version of the algorithm for working with binary data and building 3D models:

- binary file download and read;
- split data into separate profiles;
- check profiles for correct splitting;
- multiple conversion of binary data of each profile into floating point numbers (two-dimensional coordinates of points);
- stitch two-dimensional profiles into an array of 3D coordinates using a fixed step, as well as a rotation matrix (in the case of axial rotation);
- develop of a 3D cloud of points;
- remove noise by data clustering.

B. Scanner Calibration

The new approach allows calibration to be carried out during the scanning process and with high accuracy to guarantee the complete absence of consequences of calibration of measuring equipment during long-term downtime and storage. This method can also be applied to devices operating on the start-stop principle and allows for quick start and preparation for measurements.

In accordance with the designation of the axes adopted by the manufacturer of the laser scanner, we assume that the 2D profile to be taken lies in the Oxz plane. Based on the features of the AK, the procedure for forming a single 3D array of coordinates of the scanned object implies the transformation of the profile coordinates from the 2D coordinate system associated with the laser scanner into the 3D world coordinate system (see Fig 4).

The transformation procedure includes three steps:

- rotate 2D profile in the Oxz plane to compensate for the angle of rotation of the laser scanner on the bracket;
- transfer of a 2D profile in the Oxz plane to compensate for the distance of the laser scanner from the axis of rotation of the turntable.
- rotate the 2D profile about the turntable rotation axis to form a 3D coordinate array.

To implement the indicated algorithm, it is necessary to consider the following parameters of the hardware complex:

- turntable motor step;
- distance from the axis of rotation of the turntable to the laser scanner;
- angle of inclination of the laser scanner relative to the plane of rotation of the table.

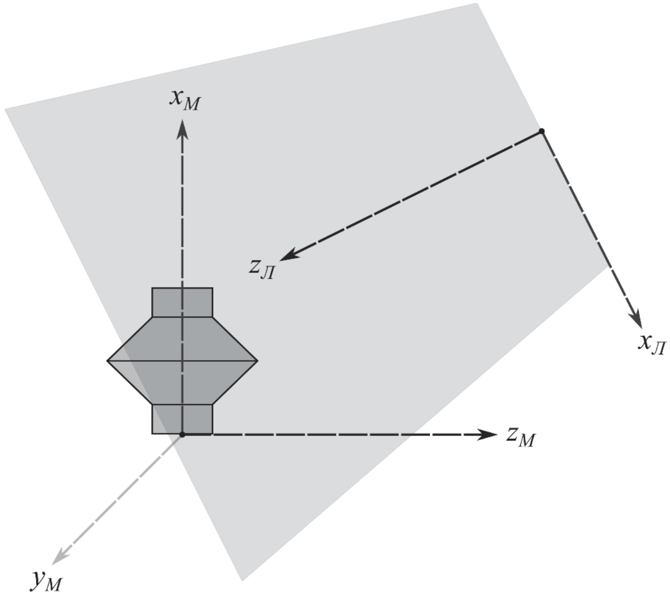

Fig. 4. Correlation of coordinate systems for the calibration sample

In addition, taking into account possible errors and backlashes when assembling the hardware complex, it is necessary to consider such additional parameters as:

- deviation of the Oxz plane from the vertical position;
- deviation of the axis of rotation of the turntable from the vertical position.

Calculation of these parameters with the required accuracy is achieved by calibrating the modules.

C. Modules Calibration

Calibration is performed by a specifically designed template printed on a 3D printer using photopolymer technology.

Turntable motor pitch calibration algorithm includes the following steps:

- caliber scan;
- formation of a list of two-dimensional profiles;
- comparison of the coordinates of the points of the zero profile with the coordinates of the points of each subsequent profile;
- search for the n profile with a minimum deviation from zero;
- step calculation.

Algorithm for calibrating the distance from the axis of rotation of the turntable to the laser scanner includes the following steps:

- caliber scan;
- formation of a point cloud from 2D profiles using the parameters of the hardware complex in the initial approximation;
- calculation of the maximum diameter of the caliber;
- comparison of the maximum diameter of the caliber with the reference value;

- calculation of the deviation of the maximum diameter of the caliber from the reference one;
- adjusting the distance from the axis of rotation of the turntable to the laser scanner based on the received deviation.

Algorithm for calibrating the angle of inclination of the laser scanner relative to the plane of rotation of the table includes the following steps:

- determination of coordinates of reference points 1, 2 on the profile in the coordinate system associated with the laser scanner;
- search for the angle of inclination.

D. Building a Point Cloud

After the modules calibration, the 2D profiles obtained as a result of scanning are transformed into a 3D array of coordinates, and then into a point cloud. For the greatest coverage of the surface of the part, scanning is performed from two angles.

With the help of the point cloud registration algorithm, fragmentary point clouds are assembled into a single point cloud (see Fig. 5).

Fig. 5. Building a point cloud

E. Inspection of Geometric Characteristics

Inspection of the geometric characteristics of the object is performed by estimating the minimum and maximum coordinates of the point cloud along the axes of the rectangular coordinate system Oxyz . In the simplest case, the lengths of the sides of the smallest possible parallelogram are calculated, which entirely encloses the measured cloud of points. To be able to measure an individual point cloud element, it is necessary to cut off the target element, and then measure the resulting fragment.

The section of the point cloud is developed on the basis of the available information about the reference geometry of the object. For correct clipping of a fragment of a point cloud, it is necessary to first orient the point cloud relative to the world coordinate system.

Point cloud orientation algorithm relative to the world coordinate system includes the following steps:

- determine the smallest possible parallelogram as initial one, which entirely encloses the measured cloud of points;
- build a target parallelogram of the same size in the axes of the world coordinate system (see Fig. 6);
- find the transformation that brings the source parallelogram to the target one (four vertices of the parallelogram are used as the reference points of the transformation);
- apply transformation to the point cloud.

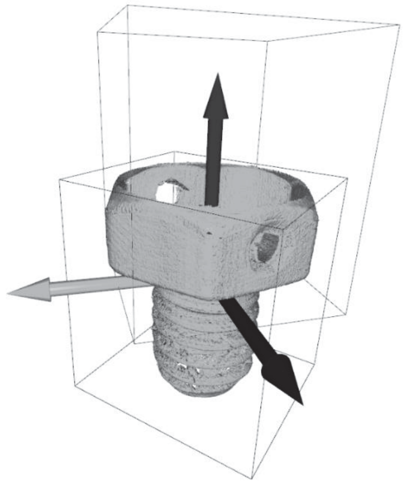

Fig. 6. Target parallelogram in the axes of the world coordinate system

Hough transform is applied to the projection of the 3D point cloud for detecting straight and curved lines in grayscale or color images. The voting procedure is applied to the parameter space, from which objects of a certain class of figures are obtained according to the local maximum in the so-called accumulative space, which is constructed when calculating the Hough transformation.

Testing in practice has shown sufficient accuracy. A comprehensive scanning of the part was carried out, both in control points according to the technological map, and in places selected by a specialist for additional analysis. Based on the test results, it was found that the 3D model obtained as a result of complex scanning has an accuracy relative to the real sample of about 10-12 microns.

VI. Intelligent Technologies Implementation

A. Automated Visual Control of Products

Under the framework of quality guarantor the proposed visual control module for product external appearance inspection was implemented to provide the quality check of the surfaces of various fasteners: bolts, screws, nuts, cotter pins, washers, pins, fingers, etc.

These parts must have the correct shape according to the design documentation and be perfectly clean. The surface should be free of external contamination and defects like oil, dirt, paint, moisture, chips, rust, scale, slag, splashes of molten metal, corrosion products, dents, scuffs, marks, cracks, etc. on separate planes of parts, small risks, dents and ripples within half of the maximum deviations in accordance with the technical requirements for the product.

Such parts are manufactured on various machines, e.g. turning, milling, drilling, stamping, etc., then cleaned of dirt and chips, lubricated with special fluids if necessary, and submitted for quality control. Quality control of parts includes heir visual inspection and measurement of parameters. An artificial neural network being installed in quality guarantor can replace the process of manual visual inspection of parts and provide an objective inspection result with quality indicators.

As part of neural network training various types of visual inspection are classified and a dataset is prepared from images of parts with examples of surface contamination and defects. For example, the system was used to identify rust (see Fig. 7).

An artificial neural network with MSDNet architecture is used here. In most cases, rust has a reddish tint to the surface color, which can be recognized by decomposing the image into a large number of layers in a non-RGB color range. The resulting image is converted to HSV format. Bitwise addition of the resulting mask and image allows you to select areas with rust and filter out parts that are not covered with rust.

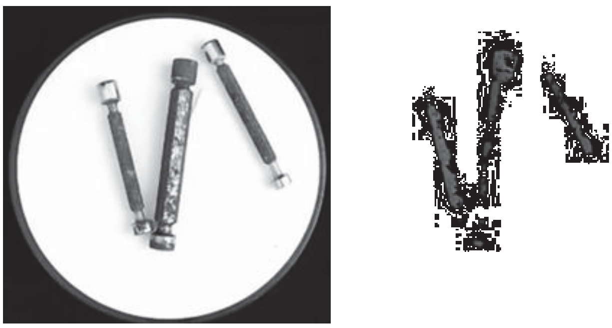

Fig. 7. Identification of rust

B. Assembly Fasteners Control

Another one problem being solved by quality guarantor is automatic verification of the presence of structural fasteners on its component parts using a convolutional artificial neural network. The solution is valid for the quality control of products, which consist of multiple elements that are fixed to each other with the help of fasteners: a bolt, a screw, a nut, a slotted nut, a stud, a cover, a safety wire (including those with a seal), a cotter pin and a lock nut, etc.

Each of the mentioned above elements is located in a specific place on the product design. To formalize these elements, a list is compiled of their locations on the product design with the required quantity. For this list, the order of execution of control operations is determined. Then all elements are marked on the 3D assembly model in virtual space. This approach provides access to the collection of datasets for hard-to-reach areas of the product, where its structural elements interfere with the free access of photographic equipment.

In accordance with the order of control of structural elements, a dataset was assembled in the size of 1842 images, including 32% of real photographic data and 68% simulated using 3D models. A convolutional neural network used in these cases has the YOLO architecture version 4.

The best result presented a recognition accuracy of 96 – 99% in 18 000 iterations.

C. Automated Sorting of Products

Quality guarantor module used for automated sorting of products provides classification of tested parts using a preliminary trained convolutional neural network. A training dataset was formed from images of mechanical production parts: bolts, screws, nuts, cotter pins, washers, pins, fingers, etc.

Four typical part types were used and they were assigned classes. The images were obtained by photographing real-life details. The number of images in the classes was evenly distributed. In order to expand the image set, it was decided to augment the original images. As a result of the operations performed, the total number of images was increased to 2259 images. The training set included 2178 images, while 81 images were included in the test set.

Training was performed using an Nvidia RTX 2070 video card. During the training, weights for the neural network were obtained As a result, 31% of real images and 69% of augmented ones were used. The best recognition result was obtained in 14000 iterations. Fig. 8 shows an example of details' recognition.

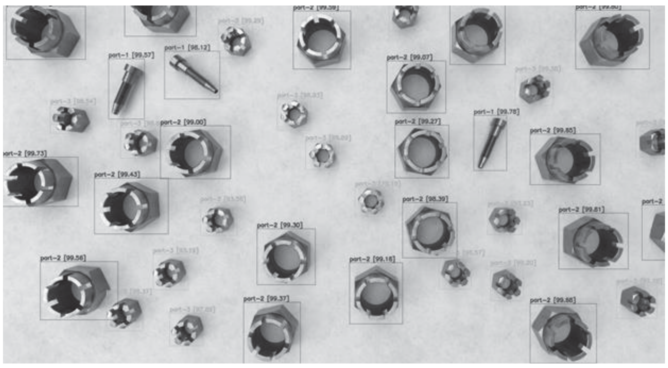

Fig. 8. Mechanical production parts and units recognition and classification

D. Inspection of Internal Surfaces and Recognizing of Holes

Visual control module for product internal inspection based on a visual camera-endoscope was implemented to control products with internal channels. It provides checking the quality of product surfaces, including internal holes, and determining the correctness of the intersections of holes.

The internal channels of products are made using drilling machines. During the processing, various defects in the internal surfaces appear, and the lubricant or chips remaining after processing can adhere tightly to the walls and are difficult to remove. The presence of defects and material residues after processing can affect the functionality of the product.

To visualize the operation of the neural network, the "gradcam ++" approach was used, which uses gradients to form a heat map, and this map can be an indicator of what the neural network pays attention to, and what influences the classification the most. The results are presented in Fig. 9 – 10.

Also, the neural network was trained to recognize intersecting holes (see Fig. 11). The training involved 2213 images, among which 2166 images were used for training. As a result of training, the result of the mAP metric was 89%. The figures below show the result of the trained neural network.

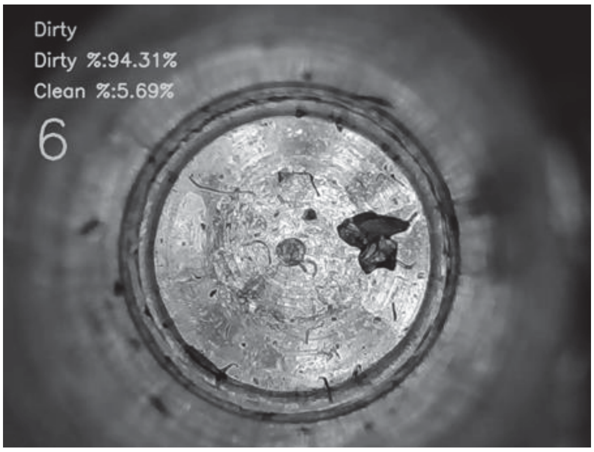

Fig. 9. Identification of contamination

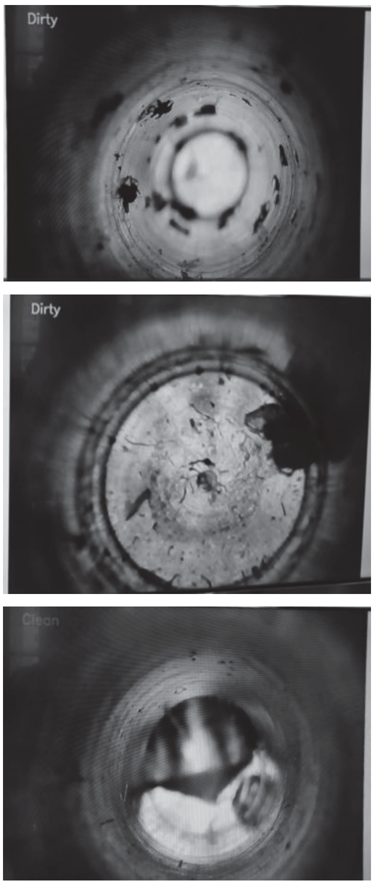

Fig. 10. Dirty (top) and clean (bottom) inner surfaces identification

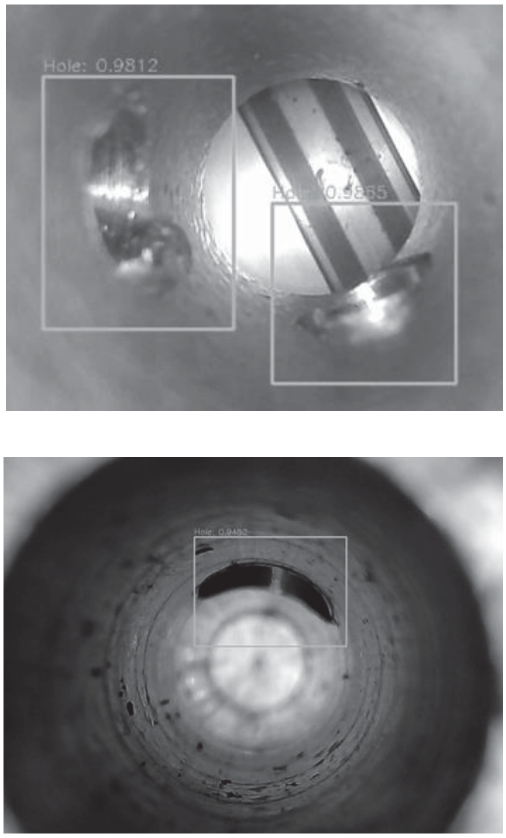

Fig. 11. Holes and their intersections recognition

E. Manual Operations Control

A challenging area of application for a quality guarantor is the inspection of manual operations performed by the personnel of a manufacturing enterprise. In this case, the use of specialized modules is not required, and video recording can be done with standard video cameras installed at workplaces.

The main idea of quality control in this case is that the machine vision system can detect standard patterns of repetitive manufacturing operations. These operations can be formalized by the technological process, or recorded as a result of the analysis of the results of video filming of the actions of highly qualified personnel with extensive experience.

An example of intelligent manual operations control is illustrated by Fig. 12 representing the process part–radial compressor (turbo machinery) assembly operation. Artificial neural network provides image recognition of the objects and actions and their matching with a corresponding description in a digital technological process.

Intelligent system for manual operation control are close in use cases and functionality to interactive user guides that also implement Augmenter Reality (AR) applications for decision making support at certain stages of operating processes. Video panels or AR goggles in this case are used to present the corresponding contextual information to an operator.

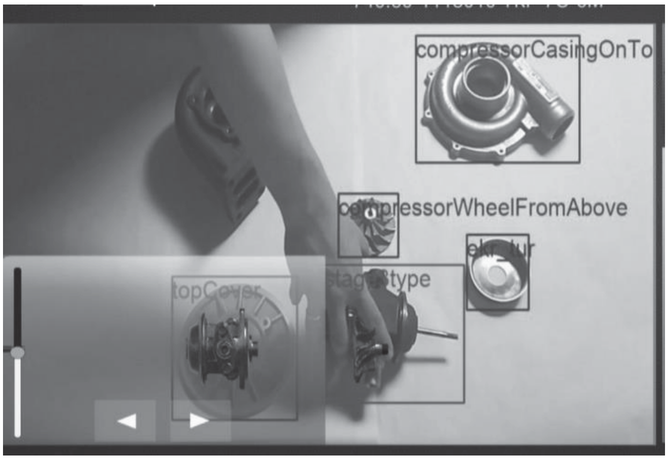

Fig. 12. Manual operations control

The result of the module is the control of the assembly of a complex product according to the technological map in real time, as well as the ability to generate interactive prompts with instructions and further steps of assembly or correction.

VII. Conclusion

Implementation of quality guarantor architecture and design technique based on covering the production process with the modules of external and internal visual quality control allows improving the quality indicators due to systematic and targeted application of artificial intelligence. As a result, it is possible to significantly expand the range of application of machine vision systems for quality control at modern manufacturing enterprises.

The existing results confirm the great prospects for replication of this solution in mechanical engineering. Further research in this area is related to improving the accuracy and reliability of defect detection at different stages of production processes.

Implementation of the quality guarantee allows not only to ensure the detection of defects in the workplace, but also to identify deviations in the performance of technological operations, generate recommendations for improving the efficiency of their implementation, and generate input data for business analysis of production processes within the enterprise global quality management system.

References

[1] S. Anand and P. Loganathan, *A Guide for Machine Vision in Quality Control*. Chapman and Hall/CR, 2020, 208 p.

[2] M. Ghobakhloo, "The future of manufacturing industry: a strategic roadmap toward Industry 4.0", *Journal of Manufacturing Technology Management*, 29, 2018, pp. 910-936.

[3] P. Osterrieder, L. Budde and T. Friedli, "The smart factory as a key construct of industry 4.0: a systematic literature review", *International Journal Of Production Economics,* 221, 2020, 107476.

[4] S. Mandapaka, C. Diaz, H. Irisson, A. Akundi, V. Lopez and D. Timmer, "Application of automated quality control in smart factories - a deep learning-based approach", *2023 IEEE International Systems Conference (SysCon)*, Vancouver, BC, Canada, 2023, pp. 1-8.

[5] F.D. Turek, "Machine vision fundamentals, how to make robots see", *NASA Tech Briefs*, 35 (6), 2011, pp. 60-62.

[6] C. Steger, M. Ulrich and C. Wiedemann, *Machine vision algorithms and applications*. Weinheim: Wiley-VCH, 2nd ed., 2018, 516 p.

[7] J. Beyerer, F.P. Leon and C. Frese, *Machine vision. Automated visual inspection: theory, practice and applications*. Berlin: Springer. 2016, 798 p.

[8] D. Moru and D Borro, "A machine vision algorithm for quality control inspection of gears", *The International Journal of Advanced Manufacturing Technology*, 106 (2), 2020, pp. 105-123.

[9] A. Akundi and M. Reyna, "A machine vision based automated quality control system for product dimensional analysis", *Procedia Computer Science*, Vol. 185, 2021, pp. 127-134.

[10] M.M. Ali, N. Hashim, S.A. Aziz and O.O. Lasekan, "Quality inspection of food and agricultural products using artificial intelligence", *Advances in Agricultural and Food Research Journal*, Vol. 2, No. 2, 2021, pp. 1-17

[11] J. Han, T. Li, Y. He and Q. Gao, "Using machine learning approaches for food quality detection", *Mathematical Problems in Engineering*, 6852022, 2022, pp. 1-9.

[12] R. Kesharwani, C.H. Dagli and Z. Sun, "Application of neural network in shop floor quality control in a make to order business", *Procedia Computer Science*, 95, 2016, pp. 209-216.

[13] R. Ozdemir and M. Koç, "A quality control application on a smart factory prototype using deep learning methods", *Proceedings of CSIT 2019*, 2019. pp. 46-49.

[14] O. Surnin, P. Sitnikov, A. Gubinkiy, A. Dorofeev, T. Nikiforova, A. Krivosheev, V. Zemtsov and A. Ivaschenko, "Augmented reality implementation for comfortable adaptation of disabled personnel to the production workplace", *Proceedings of the 35th Annual European Simulation and Modelling Conference*, 2021, pp. 64-69.

[15] G. Wang, A. Ledwoch, R. Hasani, R. Grosu and A. Brintrup, "A generative neural network model for the quality prediction of work in progress products", *Applied Soft Computing*, 85, 2019, pp. 9-12.

[16] C. Kyriakopoulos, I. Gialampoukidis, S. Vrochidis and I. Kompatsiaris, "Adaptive quality diagnosis framework for the production line in a smart manufacturing environment", *Machines*, 11. 2023, 499.

[17] P. Thomas, M.-C. Suhner, E. Zimmermann, H. El Haouzi, A. Thomas and M. Noyel, "Neural network inverse model for quality monitoring - application to a high quality lackering process", *Proceedings of IJCCI'17 9th International Joint Conference on Computational Intelligence*, 2017, pp. 186-191.

[18] M. Malesa and P. Rajkiewicz, "Quality control of PET bottles caps with dedicated image calibration and deep neural networks", *Sensors*, 21(2), 2021, 501.

[19] C.A. Escobar and R. Morales-Menendez, "Machine learning techniques for quality control in high conformance manufacturing environment", *Advances in Mechanical Engineering*, Vol. 10 (2), 2018, pp. 1-16.

[20] A. Ivaschenko, O. Golovnin, V. Avsievich and P. Sitnikov, "Intelligent quality guarantor model for computer vision based quality control", Lecture Notes in Networks and Systems, Vol. 628, Springer, Singapore, 2023, pp. 1-9.

[21] W. Yuan, "Accuracy comparison of YOLOv7 and YOLOv4 regarding image annotation quality for apple flower bud classification", AgriEngineering, Vol. 5, 2023, pp. 413-424.