Vol. 01, No. 04 (2023) 191-198, doi: 10.61552/JEMIT.2023.04.004 - http://jemit.aspur.rs

IDENTIFICATION OF PRODUCT NON-CONFORMITIES USING COMPUTER VISION ALGORITHMS

Djordje Mijailovic [1]
Aleksandar Djordjevic
Miladin Stefanovic
Milan Eric

Received 02.03.2023.
Accepted 11.09.2023.

Keywords:

Industry 4.0., Quality 4.0. Cloud, Computer vision, OpenCV, Hough transform, Real time

A B S T R A C T

The implementation of computer vision in the process of identifying non-conforming products, as well as the application of technologies based on Internet networks, deep learning, large databases within the manufacturing industry leads to the emergence of quality 4.0. Today, the application of computer vision as well as non-conformity detection algorithms in the manufacturing industry can be seen as technological pillars of quality 4.0, which is in direct connection with the company's operations. The main goal of the work is the development of a system for identifying non-compliant products within the manufacturing industry, where the focus is on the application of technologies based on computer vision. The secondary goal of the work refers to the reduction of the necessary funds for the implementation of the system on production machines, the development of a universal, flexible system, where the timely identification of non-compliant products will reduce the company's losses.

1. INTRODUCTION

Timely identification of the number of non-compliant products within the production industry, where the focus is on each production machine as well as the product itself, leads to a number of advantages on the way to successful business. Currently, a number of ways to identify non-compliant products can be found on the market. Of course, depending on the production of a specific product, the method of identifying non-conformity, i.e. the application of a certain technology, also depends. Viewed from the aspect of surface non-conformity of the product, identification can be done using technology based on computer vision (Yu et al., 2019). The advantage of applying this technology compared to others is the adaptability of the system, independence, accuracy, response time considering that they represent real time systems, as well as the price of such systems (Ligarski 2012). The implementation of computer vision in the process of identifying product non-conformities implies the use of algorithms that will analyze and detect images, as well as a number of libraries that are necessary both for calculations and for linking algorithms, the most significant being the use of the OpenCV library (Chai et al., 2021). The basic processes of computer vision are data acquisition and data processing, problems that may occur in the data acquisition process relate to external factors that may affect the quality of the collected data, while problems in data processing may relate to the complexity of the applied algorithms as well as the time that is required for the processing process itself. Considering that this technology can be applied for the detection of surface inconsistency, and according to the algorithms used, it can be divided into systems developed for the detection of contours, objects, color, text, dimensions. Certainly, the application of computer vision in the process of identification of non-compliant products brings a number of advantages compared to traditional methods that were based on the training of employees or experts in the field of quality and who performed the

[1] Corresponding author: Djordje Mijailovic
Email: mijailovicdjordje3@gmail.com

identification process visually.
The main goal of this study stems from the need to develop a quality control system that will work independently without the assistance of an employee. Although there are a large number of researchers who have done case studies in the field of quality control using computer vision technology, there is still a need for further development of such systems that will focus on contour detection in the shortest possible time interval and with minimal hardware requirements. Secondary objectives relate to the storage of data collected by this case study, data analysis. The advantages of the application of this case study compared to the traditional methods of identification of product non-conformity are reflected in the timely operation of the system, the reduction of the production of non-conforming products, the availability of data, and the reduction of production errors. The contributions of this study derive from the advantages of implementing algorithms that are related to the time required for contour detection in the specific case of circle detection, system training that requires a few minutes, and its adaptability.
Within this paper, a review of the literature will be presented, in which terms related to product non-conformity itself, identification and classification, and non-conformity management methods will be defined. The technologies applied within this study as well as the system developed by this study for the purposes of identifying product non-conformities, which arise from the needs that are a consequence of real problems in the manufacturing industry.

2. LITERATURE REVIEW

2.1 Non-compliance

A non-compliant product is any product that deviates from the quality defined by the standard, that is, from the requirements of the customer or user of the product or service. Observed from the aspect of non-conformity of the product that can occur during its production itself, it can be concluded that a larger number of non-conformities or deviations from quality requirements can be detected on one product at some point. The increased production of non-compliant products directly affects the company's profit, primarily through increased losses, among the biggest losses are certainly the raw materials needed for the production of products, additional time spent by employees, additional energy (Liepiņa et al., 2014;). In order for the company not to get into a situation that could endanger its business, it is necessary to adhere to the quality of the product defined by the standard, which further leads to the need for quality control, i.e. continuous checks to see if there are non-compliant products in production (Powell et al., 2021;). It certainly does not mean that even if a product's non-conformity is observed, it cannot be used further, in some cases it is possible to refine it, and that is if it is a minor non-conformity, while in the case of a major non-conformity, the product is declared scrap and as such cannot continue the further process (Hoyle 2009). Of course, if it is possible to finish the product, it is further sent to the finishing process, but this can significantly affect the price of its production (Hoyle 2009).

2.2. Identifying non-conforming products in the industry

The identification of non-conforming products within the manufacturing industry can be seen as a process of determining deviations from the product quality requirements of a company, and it can happen on the production machine itself, the production line, or on the packaging of the product as a final process during the life cycle of the production of a product (Donauer et al., 2015; Powell et al., 2021;). Although the process was successfully implemented and the product nonconformity was identified, the identification of the cause that led to the nonconformity is also of great importance, preventing the cause that led to the nonconformity directly affects the further flow of production (Ligarski 2012; Powell et al., 2021 ;). Deviations can be in the form of surface inconsistencies or inconsistencies that can appear in the structure of the material, which leads to different methods of identifying inconsistencies and to different technologies that can be used in the process of identifying inconsistencies (Koucha et al., 2021;). Successful and timely identification of non-compliant products directly affects the reduction of scrap, savings in production time, and losses that occur due to product processing (Koucha et al., 2021;).

2.3. Methods of identification of product non-conformity

The basic methods of identification of inconsistencies refer to surface inconsistencies and internal inconsistencies, which are based on the structure of the material. External defects are those located on the surface of the product, most often caused by machine failure or carelessness of employees, and refer to minor damage such as scratches, paint, text, etc. While internal defects are mainly based on the discovery of trapped air during metal casting, which can later result in cracking of the product. The methods of detecting internal non-conformities that are most often applied today are radiation methods, ultrasound methods (Yang et al., 2020). Using ultrasonic methods based on the propagation of the ultrasonic wave, it is possible to conclude in which region the inconsistencies are found, as well as the order of their magnitude (Ha et al., 2021). The beam-based method uses a beam that is passed through the material and thus the location of the defect as well as the size can be obtained (Cacace et al., 2021). While the methods of detecting surface non-conformities in small and medium-sized companies are mostly based on manual control, that is, they depend on the employee and on the basis of his knowledge and experience as well as his ability to visually recognize the defect. When it is necessary to control product dimensions or centricity, there are manual tools that can be applied that depend on the employee. The application of modern technologies such as machine vision applied for visual control brings with it a number of advantages, shorter data processing time, timeliness, accuracy (Yu et al., 2019). Of course, machine vision depends on the quality of the equipment, the algorithm used to select and recognize non-conformities, but on the other hand, after installing the system, it is independent, that is, it does not depend on the employee and his knowledge and experience, it provides data in real time (Oqaidi et al., 2021, Sivkov et al., 2020, Steenkamp et al., 2017, Chai et al., 2021). Certainly with the application of computer vision and within Industry 4.0. technologies such as deep learning and artificial intelligence are also applied for faster and more efficient non-conformity selection as well as event prediction based on system experience, cloud data storage systems, IIOT (industrial internet of things) is applied for machine control based on defined non-conformity, industrial robots as well as industrial production lines, (Cronin et al., 2021, Julian oks et al., 2021, Khan et al., 2020, Shavetov et al., 2019, Oqaidi et al., 2021, Sivkov et al., 2020, Steenkamp et al., 2017, Chai et al., 2021).

2.4. Classification of non-conformities

As the level of non-conformity of the product can differ by several different factors, it can be divided into minor non-conformities, major non-conformities and critical non-conformities (Monteiro et al., 2019; Powell et al., 2021;). Minor non-conformities are noticeable, but the product as such can be found on the market at lower prices with an indication that it deviates from the standard (Gamme et al., 2019;). Greater product non-conformity requires product rework after which the product can be forwarded to the market (Chiu et al., 2018;). Critical non-conformance represents deviations from the requirements that affect the functionality of the product, which automatically means that it cannot be used as such (Hoyle 2009). Product non-conformity can occur for several reasons, the most common of which is due to the failure of the production machine, deviation of the quality of the material from which the product is made, carelessness of employees (Chiu et al., 2018;). Product non-conformity can be expressed in several ways, the basic way is external and internal non-conformity (Chiu et al., 2018;,Monteiro et al., 2019;). External non-conformity is a deviation that is visible, it is most often damage on the surface of the product or semi-finished product in the form of scratches, deviation of shape, dimensions, text, color (Monteiro et al., 2019;). While the internal non-conformity refers to the structure of the material, if it is metal casting or plastic injection, there may be air trapped in the product itself (Gamme et al., 2019;). In order to prevent the production of non-compliant products, it is necessary to react in time, that is, if an employee notices the production of non-compliant products that occurred as a result of a machine failure, it is necessary to stop the further flow of production. It is necessary to classify non-conforming products according to the degree of non-conformity and, based on the data, proceed further in accordance with the company's policy (Gamme et al., 2019;). After the non-conformity identification process, it is necessary to mark the non-conforming products based on the classification, which refers to products that can be processed, can be sold as such, but with a note, products that are sent to scrap (Monteiro et al., 2019; Powell et al. ., 2021;). Successful classification of non-conforming products can prevent the appearance of non-conforming products on the market, which significantly affects the company's business. Marking of non-compliant products after classification should be a defined process and easy to learn for employees, so that based on a successful classification, the products will be passed on to the production flow in accordance with the performed classification.

2.5. Management of non-conformities

Successful management of non-conforming products is the basis of a company's successful production. In order to successfully manage non-compliant products, it is necessary to define product control intervals, ways of marking non-compliant products, and procedures for disposing of non-compliant products. Control intervals are directly related to the type of production, whether it is serial mass or individual, as well as by top management (Hoyle 2009). After the detection of a non-conforming product, and depending on the level of non-conformity, it is necessary to mark the product in an adequate way if it is a question of critical non-conformity, after which the product is declared as scrap and as such is further sent for destruction, in the case of major or minor non-conformity, if it is possible, it is necessary to refine the product mark the product and pass it on for further processing (Hoyle 2009; Powell et al., 2021;). The marking of non-conforming products is one of the important processes, since on the basis of the marked products, the procedure is followed, the marking differs from company to company, mostly companies practice to have an internal way of marking (Hoyle 2009).

2.6. Application of computer vision in the quality control process

Computer vision can provide a wider range of data in terms of quality control, positioning of robots in space, control of production lines as well as the products themselves, object recognition, barcode scanning (Louw et al., 2019). The quality control process can be observed in several ways, depending on the production itself, i.e. what needs to be controlled, mainly the color of the product, the text or stamp on the product that is stamped, dimensional control, quality control of the object's surface, i.e. whether there are visible damages on the surface such as scratches or in the process of forming the sheet whether it contains all the necessary openings. Also when it comes to monotonous tasks such as comparing two objects or sorting both on the industrial machine itself and on the production line, computer vision is imposed as a good technology for the mentioned application. Certainly, when it comes to precise profile measurements, which require a lot of time, the process can be accelerated with the application of computer vision. Monitoring of products throughout the entire technological process of production or within a certain technological process.

2.7. Industry 4.0.

By applying Industry 4.0 technologies. in the process of identifying product non-conformities, significant advantages can be achieved compared to manual identification (Bigliardi et al., 2020; Horváth et al., 2019). All this affects the speed of production, product quality, timeliness of data, availability of data, accuracy (Culot et al., 2020). The most important technologies of industry 4.0 that are applied in the process of non-conformity identification are: computer vision, IIOT (Industrial Internet of things), deep learning, neural networks, databases, internet networks, microcontroller platforms, programmable logic controller, cloud, embedded systems, sensor systems, distributed systems (Albers et al., 2016, Bal et al., 2019; Müller 2019; Tupa et al., 2017, Mijailovic et al., 2020).

2.8. Cloud

The storage of real-time data collected from the industry in a database that can be accessed independently of the platform or operating system is called the cloud. These systems represent one of the most important tools for the successful implementation of Industry 4.0. (Lane et al., 2016). The application of cloud systems in relation to traditional databases has a number of advantages, the most significant of which are access in real time, it lowers the necessary funds related to the maintenance of the database and the hardware part (Kolesnyk et al., 2021; Mijailović et al., 2018). In the case of the application of some other databases that require hardware systems for storing large amounts of data, they would be within the manufacturing industry (Lane et al., 2016; Murugaiyan et al., 2020), which actually represents a number of disadvantages of such a system. While in the case of cloud system application, all data is located in one place that is always available, with the fact that the lack of such systems can represent an internet connection (Lane et al., 2016).

3. CASE STUDY

This paper presents a system developed for the identification of non-conforming products or semi-products, based on the application of computer vision. In the process of identifying non-compliant products, the system, in addition to data acquisition, performs the process of detecting contours based on circles. As it is often the case that in industry, during the production process, the product contains openings for screw connections or technological openings that are further important for the product assembly process, hence the need for the development of such a system. Also the application of this system that is imposed is the product assembly process where the identification of screws can be done, it can also be applied for product selection. Based on the use of the Hough transformation, it detects circles on the semi-finished product, preventing further operation of the machine if the lack of one or more circles is identified. The system was developed to work in real time, where data is stored on the cloud, providing the possibility of accessing data in real time. Certainly, the advantages of using this system are reflected in speed, flexibility, reduction of the number of non-compliant products, precision.

3.1 System software

When it comes to starting the system for the first time, it is necessary to place the hardware on the corresponding production machine, after checking the system can be started. After the first start of the system, it can work independently, which makes the application of this technology an advantage over traditional ways of identifying non-compliant products. When the system is started, images are acquired using computer vision and the OpenCV library, then the collected data are processed using Hought's transformation, and the output of the system is data related to the number of identified circles as well as the number of compliant or non-compliant products. It is also possible to define conditions related to the number of identified circles, after obtaining the specified data they are stored on the cloud in the specific case ThingSpeak was used. The mentioned process is executed in real time, where the total time of the algorithm is 0.35 seconds for one image, which is certainly faster than the system requirements, that is, from the production machine and its process of producing one product. Certainly one of the important features of this system is adaptability, it can be moved from one production machine to another and continue working without interruption. Algorithm performance tests were performed within the premises of the university, laboratory of the quality center. In Figure 1, you can see an example of a semi-finished product that has circles on it that refer to twisted screws.

Figure 1. Example of a semi-finished product with both screws (Source: Author)

As can be seen in Figure 1, the semi-finished product contains 2 screws that were detected using the developed system. Figure 2 shows the result of the algorithm.

```
The first contour is the screw: 39 px.
The second contour is the screw: 39 px.
```

Figure 2. Result of the semi-finished algorithm with both screws (Source: Author)

Based on the results of the system algorithm, which are shown in Figure 2, it can be seen that the product is compliant. In Figure 3, you can see the non-compliant semi-product.

Figure 3. Non-compliant semi-finished product (Source: Author)

Based on Figure 3, it can be concluded that one screw is missing from the semi-finished product, which can also be seen based on the results of the algorithm shown in Figure 4.

```
The first contour is the hole for the screw: 35 px.
The second contour is the screw: 39 px.
```

Figure 4. Inconsistent product of algorithm results Source: Author

As can be seen in Figure 4, the product is non-conforming, it does not have one of the two screws. The presented data is stored on the cloud system within this system thingspeak cloud was used, an example of the stored data collected by this system can be seen in Figure 5.

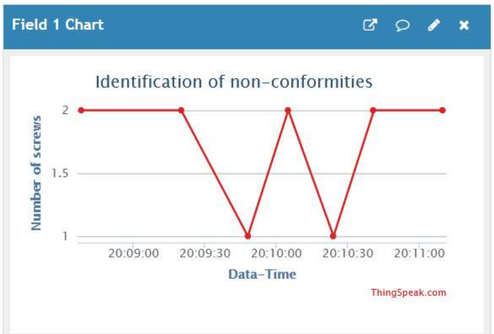

Figure 5: Data stored in the cloud Source: Author

We can additionally process and display data stored in the cloud in several ways, the advantage of cloud data is its availability.

4. DISCUSSION

The focus of the system developed in this work is on the process of identifying product non-conformities with the use of modern technologies that involve the application of computer vision. After the implementation of the system in the production industry, it brings a number of benefits compared to the traditional ways of identifying non-compliant products. Some of the advantages are reflected in the speed, accuracy, flexibility, independence of the developed system. Traditional ways of identifying non-conformities involve the interaction of an employee, i.e. the engagement of employees from the product quality sector, where there are a number of limitations and in terms of the time necessary to identify non-conformities if it is a serial production or several production machines, the time needed to form a report or the reaction that would should stop the further flow of production if there is an increased number of product non-conformities. While in the case of the application of the system developed in this work, we receive the data in real time, the reaction of the system is also in real time, we can create reports, the data is stored in the cloud and can be accessed from all platforms and operating systems and further processed. The shortcoming of this system can be seen from the aspect that it was developed for use on one production machine, while a quality expert can observe several different machines as well as different types of non-conformities. Certainly, the use of this system and timely reaction affects the further flow of production and the reduction of non-compliant products.

5. CONCLUSION

The system developed by this case study represents a solution that should reduce the production of non-conforming products created in production, most often caused by a machine failure or error, thus satisfying the initial goal of the study. The increased number of non-compliant products directly affects customer satisfaction as well as costs, which certainly represents another goal for the development of this system. Timely reaction of the system is essential in terms of stopping the further flow of production of non-conforming products, which directly affects the production time.

The results of the study, which were stored on the cloud, were presented. The system has limitations related to the application itself, the developed system is used to identify contours that represent circles, which means that it cannot be used for contours of other shapes. Certainly the developed system satisfies the initial goal where the focus was on the detection of contours representing circles. This study presents a unique solution for the application of software used for identification, which is based on the implementation of the Hough transform and the training of the system, which involves defining the basic parameters related to the number of contours and their size. Further directions of this study will go towards the development of a system that will be able to detect a larger number of different contours on one product.

References:

Albers, A., Gladysz, B., Pinner, T., Butenko, V., &Stürmlinger, T. (2016). Procedure for defining the system of objectives in the initial phase of an industry 4.0 project focusing on intelligent quality control systems. *Procedia CIRP*, 52, 262-267. DOI: 10.1016/j.procir.2016.07.067

Bal, H. Ç., &Erkan, Ç. (2019). Industry 4.0 and competitiveness. Procedia Computer Science, 158, 625-631. https://doi.org/10.1016/j.procs.2019.09.096

Bigliardi, B., Bottani, E., & Casella, G. (2020). Enabling technologies, application areas and impact of industry 4.0: a bibliographic analysis. *Procedia Manufacturing*, 42, 322-326. DOI: 10.1016/j.promfg.2020.02.086

Cacace, S., Giacomazzi, S., &Semeraro, Q. (2021). Estimation of the accuracy of measurement of internal defects in X-ray Computed Tomography. *Procedia CIRP*, 99, 284-289. DOI: 10.1016/j.procir.2021.03.042

Culot, G., Orzes, G., Sartor, M., &Nassimbeni, G. (2020). The future of manufacturing: A Delphi-based scenario analysis on Industry 4.0. *Technological Forecasting and Social Change*, 157, 120092. https://doi.org/10.1016/j.techfore.2020.120092

Chai, J., Zeng, H., Li, A., & Ngai, E. W. T. (2021). Deep learning in computer vision: A critical review of emerging techniques and application scenarios. *Machine Learning with Applications*, 6, 100134. DOI: 10.1016/j.mlwa.2021.100134

Chiu, S. W., Wu, H. Y., Chiu, Y. S. P., & Hwang, M. H. (2018). Exploration of finite production rate model with overtime and rework of nonconforming products. *Journal of King Saud University - Engineering Sciences*, 30(3), 224-231. DOI: 10.1016/j.jksues.2017.12.002

Cronin, C., Conway, A., & Walsh, J. (2019). Flexible manufacturing systems using IIoT in the automotive sector. *Procedia Manufacturing*, 38, 1652-1659. DOI: 10.1016/j.promfg.2020.01.119

Donauer, M., Peças, P., &Azevedo, A. (2015). Identifying nonconformity root causes using applied knowledge discovery. *Robotics and Computer-Integrated Manufacturing*, 36, 84-92. DOI: 10.1016/j.rcim.2014.12.012

Horváth, D., & Roland, Zs. Szabó. (2019). Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technological Forecasting and Social Change*, 146, 119-132. DOI: 10.1016/j.techfore.2019.05.021

Gamme, I., &Lodgaard, E. (2019). Organizational or system boundaries; possible threats to continuous improvement process. *Procedia CIRP*, 79, 505-510. DOI: 10.1016/j.procir.2019.02.107

Hoyle, D. (2009). Part 7 Complying with ISO 9001 Section 8 Requirements on Measurement, Analysis and Improvement. In ISO 9000 Quality Systems Handbook - updated for the ISO 9001:2008 standard (Sixth Edition) Using the standards as a framework for business improvement (pp. 553-561). DOI: 10.1016/B978-1-85617-684-2.00055-4

Kolesnyk, O., Bubeník, P., &Čapeka, J. (2021). Cloud platform for learning factories. *Transportation Research Procedia*, 55, 561-567. DOI: 10.1016/j.trpro.2021.07.022

Koucha, Y., Forbes, A., & Yang, Q. P. (2021). A Bayesian conformity and risk assessment adapted to a form error model. *Measurement: Sensors*, 18, 100330. DOI: 10.1016/j.measen.2021.100330

Müller, M. J. (2019). Contributions of Industry 4.0 to quality management - A SCOR perspective. IFAC-PapersOnLine, 52(13), 1236-1241. DOI: 10.1016/j.ifacol.2019.11.367

Monteiro, C., Ferreira, P. L., Fernandes, O. N., Silva, F. J. G., &Amaral, I. (2019). Improving the Machining Process of the Metalwork Industry by Upgrading Operative Sequences, Standard Manufacturing Times and Production Procedure Changes. *Procedia Manufacturing*, 38, 1713-1722. DOI: 10.1016/j.promfg.2020.01.106

Mijailovic, Dj., Karabasevic, D., & Stanujkic, D. (2018). Development of the System For Monitoring Ambiental Factors by Applying Arduino Platform. *Trends in business*, 12, 37-45. DOI: 10.5937/TrendPos1802037M

Mijailovic, Dj., Djordjevic, A., Stefanovic, M., Vidojevic, D., Gayiyulina, A., & Projovic, D. (2021). A Cloud-Based with Microcontroller Platforms System Designed to Educate Students within Digitalization and the Industry 4.0 Paradigm. *Sustainability*, 13(22), 12396. DOI: 10.3390/su132212396

Murugaiyan, P., Ganeshkumar, C., & Sugundan, N. (2020). Technological implication and its impact in agricultural sector: An IoT Based Collaboration framework. *Procedia Computer Science*, 171, 1166-1173. DOI: 10.1016/j.procs.2020.04.125

Oqaidi, M., AitAbdelouahid, & MarzakAbdelaziz, R. (2021). Logical Computer Vision on IOT. *Procedia Computer Science*, 191, 505-510. DOI: 10.1016/j.procs.2021.07.065

Oks, S. J., Zöllner, S., Jalowski, M., Fuchs, J., & Möslein, M. K. (2021). Embedded vision device integration via OPC UA: Design and evaluation of a neural network-based monitoring system for Industry 4.0. *Procedia CIRP*, 100, 43-48. DOI: 10.1016/j.procir.2021.05.007.

Lane, T., & Schaefer, D. (2016). Software-defined Cloud Manufacturing for Industry 4.0. *Procedia CIRP*, 52, 12-17. DOI: 10.1016/j.procir.2016.07.041.

Louw, L., & Droomer, M. (2019). Development of a low-cost machine vision-based quality control system for a learning factory. *Procedia Manufacturing*, 31, 264-269. DOI: 10.1016/j.promfg.2019.03.042.

Ligarski, M. J. (2012). Problem identification method in certified quality management systems. *Quality & Quantity*, 46(1), 315-321. DOI: 10.1007/s11135-010-9356-2.

Liepiņa, R., Lapiņa, I., & Mazais, J. (2014). Contemporary issues of quality management: Relationship between conformity assessment and quality management. *Procedia - Social and Behavioral Sciences*, 110, 627-637. DOI: 10.1016/j.sbspro.2013.12.907.

Powell, D., Eleftheriadis, R., & Myklebust, O. (2021). Digitally enhanced quality management for zero defect manufacturing. *Procedia CIRP*, 104, 1351-1354. DOI: 10.1016/j.procir.2021.11.227.

Shavetov, V. S., Merkulova, I. I., Ekimenko, A. A., Borisov, I. O., & Gromov, S. V. (2019). Computer vision in control and robotics for educational purposes. IFAC-PapersOnLine, 52(9), 127-132. DOI: 10.1016/j.ifacol.2019.08.136.

Steenkamp, L. P., Hagedorn-Hansen, D., & Oosthuizen, G. A. (2017). Visual management system to manage manufacturing resources. *Procedia Manufacturing*, 8, 455-462. DOI: 10.1016/j.promfg.2017.02.058.

Sivkov, S., Novikov, L., Romanova, G., Romanova, A., Vaganov, D., Valitov, M., &Vasiliev, S. (2020). The algorithm development for operation of a computer vision system via the OpenCV library. *Procedia Computer Science*, 169, 662-667. DOI: 10.1016/j.procs.2020.02.193.

Tupa, J., Simota, J., & Steiner, F. (2017). Aspects of risk management implementation for Industry 4.0. *Procedia Manufacturing*, 11, 1223-1230. DOI: 10.1016/j.promfg.2017.07.248.

Yang, J., Li, S., Wang, Z., Hao, D., Wang, J., & Tang, S. (2020). Using deep learning to detect defects in manufacturing: A comprehensive survey and current challenges. *Materials*, 13(24), 5755. https://doi.org/10.3390/ma13245755

Yu, L., Wang, Z., & Duan, Z. (2019). Detecting gear surface defects using background-weakening method and convolutional neural network. Sensor Networks for Structural Health Monitoring, 2019, 1–13. DOI: 10.1155/2019/3140980

Djordje Mijailovic
Faculty of Engineering,
University of Kragujevac,
Serbia
mijailovicdjordje3@gmail.com

Aleksandar Djordjevic
Faculty of Engineering,
University of Kragujevac,
Serbia
adjordjevic@kg.ac.rs
ORCID: 0000-0003-2856-6578

Miladin Stefanovic
Faculty of Engineering,
University of Kragujevac,
Serbia
miladin@kg.ac.rs
ORCID: 0000-0002-2681-0875

Milan Eric
Faculty of Engineering,
University of Kragujevac,
Serbia
ericm@kg.ac.rs
ORCID: 0000-0001-8691-4863