USING NEURAL NETWORK WITH CONVOLUTION LAYER FOR AUTOMATIC QUALITY INSPECTION

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Abstract: *At traditional assembly workstations product inspection is performed manually by operators and that takes a lot of time and represents a production bottleneck. Also, due to the appearance of mental fatigue, a drop in concentration in some situations, it is almost impossible for workers to notice the appearance of defects and irregularities. Therefore, in modern assembly systems, the implementation of advanced quality control through quality inspection, visually detect the quality of a product and recognition of irregularities has a crucial role.*

The main aim of this study is to research the possibility of involving neural networks for defects' detection of parts in the production process. The research includes using images of two classes (part with defect and well done part) and training the neural network with convolution layer for automatic classification produced part. The success of applied algorithms using this methodology in automatic detection of defects and non-conformity and on this way reducing cost is 96 %. One benefit of the proposed method is the relatively small number of input data set images which enables fast implement method with new production elements.

Key words: *automatic detection of defects, Industry 4.0, neural networks, Quality 4.0, zero defects manufacturing*

1. INTRODUCTION

It is of essential importance that organizations improve product quality and on this way remain competitive and meet the changing needs and expectations of customers. Improving quality products can help organizations achieve several benefits, such as increasing customer satisfaction, improving efficiency and productivity, reducing costs, and increasing market share. The integration of quality management with the technologies of the fourth industrial revolution (Industry 4.0) enables organizations to adequately respond to the conditions in the modern dynamic business environment (globalization, turbulent market conditions, and the development of information and communication technologies). The digitalization of business processes and the development of new technologies such as artificial intelligence and machine learning have opened up new opportunities for quality improvement. These technologies can help organizations collect and analyze data, identify patterns and trends, and predict potential irregularities and non-compliance before they occur.

At traditional assembly workstations, operators perform monotonous, repetitive and tiring activities of assembling parts and components into the final product by long-term. Also, inspection of these parts is performed manually by operators and that takes a lot of time and represents a production bottleneck. Traditional quality control methods, such as sampling a single component from a lot for inspection, can lead to inconsistencies in quality and potentially result in at one side the acceptance of defective parts or on the other hand the rejection of an entire batch. This can be a costly and time-consuming process that requires allocation of financial resources and hiring additional workers with specialized skills. In addition, traditional quality management systems often rely on paper-based documentation. During the inspection, workers must pay attention to detail, which can be difficult to maintain over time. This can lead to bottlenecks in the process and delays in getting products to market.

Improving the visual quality control of products is receiving increasing attention in both industry and academia (Cabral, de Araujo, 2015). Quality 4.0 encourages a culture of continuous improvement in assembly workstations. By leveraging real-time data and insights, organizations can identify areas for improvement, implement corrective actions, and optimize their assembly processes over time. This iterative approach fosters ongoing quality enhancements and drives organizations closer to the goal of zero defects.

The full automation drastically reduces the burden on people by providing automatic control and monitoring of processes throughout the entire product life cycle (Castagnoli et al., 2021). Visual quality control systems during last years have been used to assess the quality of finished products, the quality of components and parts as well as to assess the correct functioning of workstations and production lines.
The main goal of the research paper is application of convolutional neural networks in quality inspection for detection of defects parts in the assembly process. The research includes using images of two classes (part with defect and well done part) and training the neural network with convolution layer for automatic classification produced part. Neural networks are a powerful tool in improving quality control processes by automating inspections, reducing human error, and increasing efficiency. Convolutional neural networks (CNNs) are a special type of neural networks with one or more convolution layers. The convolutional layers are responsible for extracting relevant features from the input data, while the pooling layers reduce the spatial dimensions of the feature maps, thus providing spatial invariance to small variations. CNNs are widely used in quality control. However, it is important to properly train and validate convolutional neural networks to ensure their accuracy and reliability.

2. MATERIALS AND METHODS

Real time data acquisition about product quality not only contributes to prevent products with defects but can also contributes to continuous improvement of assembly processes. This is of particular importance in the medical or automobile industry, the aim is often to realize a 100% quality inspection.
Industry 4.0 has brought about significant changes in quality inspection, what is known as Quality 4.0. Quality 4.0 refers to the use of digital technologies to improve quality management, inspection, and control in quality inspection processes.
The process of digitalization and improvements in industry has the tendency to automatize the whole process from beginning to end. The activities with this aim cannot be performed simultaneously for all parts of the system. This should only be done in stages and in a one by one basis, regarding the parts of the system part of system. According to (Rojko, 2017) costs in production and quality management can be reduced by 10-30% by implementing new Industry 4.0 technologies.
A good candidate for automatization is quality control (Schumacher, Nemeth & Sihn, 2018; Tortoella & Fettermann, 2017) on assembly workstation. The reason for this is availability of tools which are enough in visual perception recognition which include using cameras and AI system for classification. The most promising are artificial intelligence algorithms, including in particular deep machine learning algorithms based on neural networks, like in paper (Żabiński et al., 2019).
In the context of Industry 4.0, quality inspection is no longer limited to manual inspection and control by humans. Instead, it involves the use of digital technologies (Internet of Things, big data analytics, machine learning, and artificial intelligence) to collect, analyze, and interpret data in real-time. This enables manufacturers to identify defects and anomalies early in the production process and make necessary adjustments to improve product quality. Machine vision algorithms can be used in a wide range of application such as vision inspection, quality control and process monitoring (Bahaghighat, Motamedi, 2018; Pithadiya et al., 2010).
The focus of the paper (Weimer et al., 2016) is the proposal of a novel deep CNN architecture to detect defects, which takes all types of defect free and defective samples together as the input. In paper (Hoo-Chang et al., 2016.) CNN architectures within a deep learning framework that solve the shortcomings of the existing machine learning approaches were presented. Also, CNNs have recently been successfully applied to industrial surface inspection (Masci et al., 2012; Soukup, Huber-Mörk, 2014). In some research papers convolutional neural networks were used for analysis of measurement results in an intelligent condition monitoring system.
In this research paper convolutional neural networks were used in quality inspection for detection of defects parts in the assembly process. In this research the algorithms with CNNs for image classification process are presented. For training of neural network two database of 200 images. Half of the images were of well-done parts, while the other half were of parts with defects. It's important to note that the images were captured under the same conditions, which is crucial for the success of algorithms when dealing with a relatively small number of input images.
The process of collecting and grouping the images into two classes (well-done parts and parts with defects) was done manually. This manual classification ensured that the network received labeled training data, where each image was associated with the correct class label.
In the Figure 1 and 2 are shown the part with and without mistake respectively.

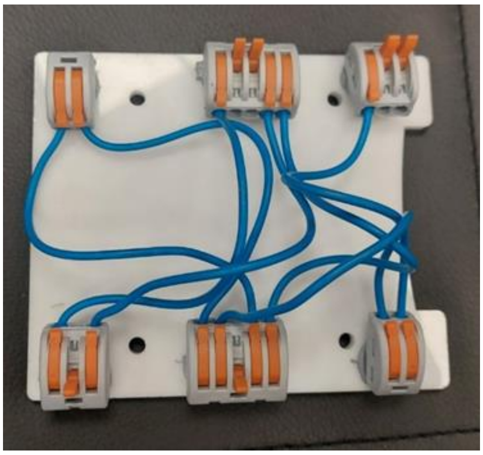

Figure 1: Correct part

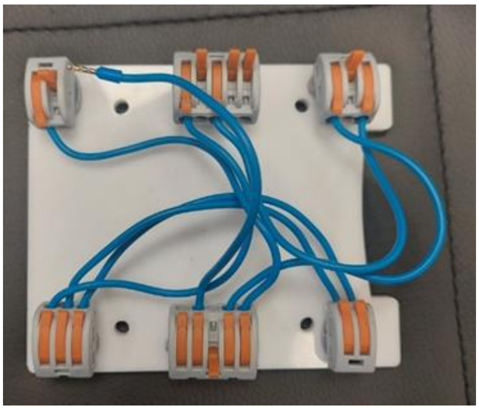

Figure 2: Part with mistake

The images were recorded in the same conditions; environmental brightness, background color, camera position and specimen orientation. All this conditions are necessary to provide well recognition quality with less number of training images. For this purpose we used 100 images per both classes. The data set is divided into part for training, testing and validating of algorithms.

By training the CNNs on this labeled dataset, the network learns to identify patterns and features in the images that distinguish between well-done parts and defective parts. The trained CNN can then be used to classify new, unseen images and identify whether they belong to the well-done or defective class, providing a means for automated quality inspection in the assembly process.

Key benefits of using CNNs for defect detection are:

- CNNs excel at learning hierarchical representations of images, allowing them to automatically extract relevant features from raw visual data. This ability makes CNNs well-suited for recognizing patterns, shapes, and textures that are indicative of defects in assembly parts.
- CNNs leverage convolutional layers that use filters to detect local patterns in images. By applying these filters across the image, CNNs can capture local features that are crucial for identifying defects. This property is especially useful when defects are characterized by specific local irregularities or variations.
- CNNs can handle variations in lighting conditions, orientations, and scales, which are common challenges in quality inspection. Through the learning process, CNNs can generalize and recognize defects even in instances where there are slight variations in appearance.

In the Figure 3. the neural network architecture is presented.

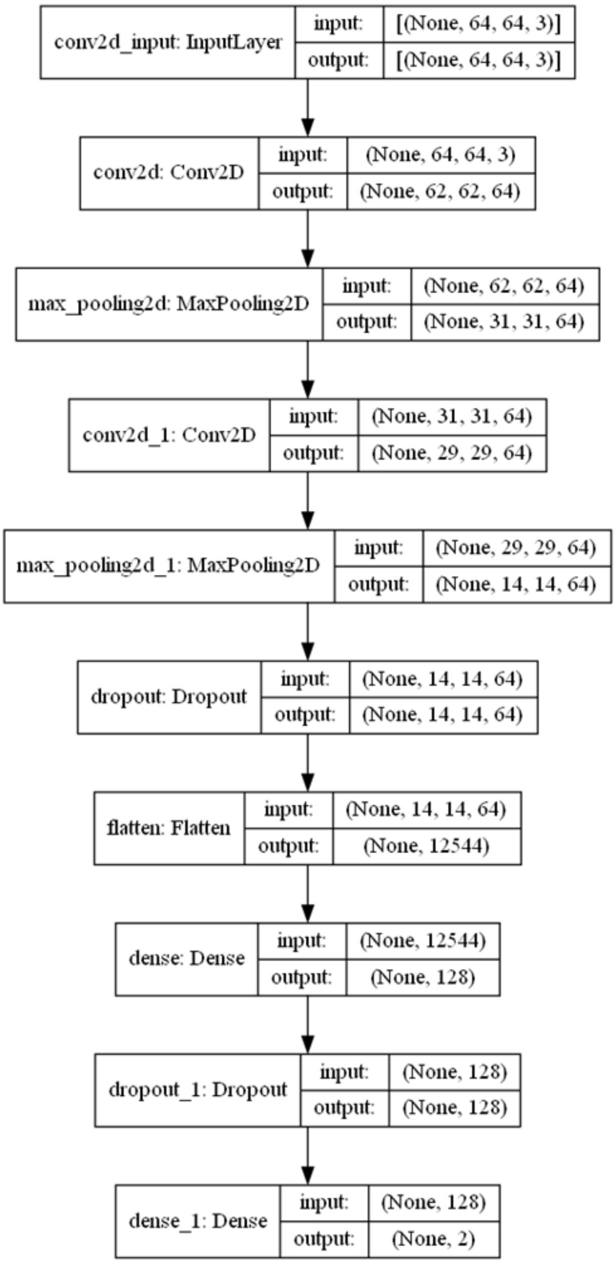

Figure 3: Structure of neural network used in research

3. RESULTS AND DISCUSSION

The neural network consists of a number of convolution layers. The first input layer accepts images whose size is resized at 64x64 pixels. During data propagatione the data dimensions are reduced. At the end, the result layer has only two outputs. This output values are connected with results classes. According to this, value image is assigned to the corresponding class in a way in which a greater value means that the image belongs to corresponding class.
The accuracy of the presented architecture with given data set is 96 % and training is performed relatively fast, around 15 minutes using standard laptop with Intel i3 with 2.3 GHz and 8 GB of RAM.

4. CONCLUSIONS

Poor product quality has a negative impact on the operational and financial performance of the organization (Kumar et al., 2018). Furthermore, it can negatively affect the company's reputation (Jun et al., 2020).

Achieving zero defects in assembly workstations is a key goal of many manufacturing organizations. The concept of Quality 4.0 has emerged as a way to optimize quality control and improve the efficiency of assembly processes. Quality 4.0 incorporates the principles of Industry 4.0, which refers to the integration of digital technologies and data-driven approaches into manufacturing. The use of Industry 4.0 technologies (such as computer vision, machine learning, and augmented reality) in assembly workstations has the potential to reduce defects and improve overall product quality. By using that advanced technologies, inconsistencies and irregularities can be identified and corrected early in the assembly process.
During the manual inspection of parts, components and the final product, errors often appear, and in some situations (eg, when production rates are high) manual inspection is impractical. So, it is necessary to apply new methods of monitoring and controlling product quality, which would be based on AI algorithms. Convolutional neural networks can help improve quality control processes by automating inspections and thus contribute to reducing human error and increasing control efficiency through identifying product defects through image analysis. However, it is important to properly train and validate neural networks to ensure their accuracy and reliability.
In this study the algorithms with CNN for image classification process are presented. The CNN has a relatively simple architecture with a number of convolution layers. For training of neural network two database of 200 images were used with half of images with well-done part and with other half parts with damages. The images were taken at the same condition, which is important for the success of algorithms with a relatively small number of input images. This causes relatively fast performing training. The study shows the ability to apply this type of algorithms in assembly process.
The improvements of the method could be in using a different architecture of CNN and with a larger database of images. Future research directions are related to the integration of this method with some robot systems for mechanical classification.

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