DETECTION OF ANOMALIES ON THE SURFACE OF WORKPIECES PRODUCED ON CNC MACHINES

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Abstract: *Poor working conditions, insufficient technology, and other factors can all have a substantial impact on the quality of manufactured components throughout the CNC manufacturing process. Poor quality is usually obvious in the form of surface abnormalities among work item flaws. Detecting these flaws guarantees both a defined quality and a high qualifying percentage. A non-manual visual inspection strategy for anomaly identification is necessary to overcome these challenges. Visual inspection automation in industrial products, such as defect inspection and anomaly recognition, is a crucial task in computer vision. As a result, ASAD (Autonomous workpiece surface anomalies detection) based approaches have grown in popularity among manufacturers for surface anomaly detection because they provide an efficient solution to address the disadvantages of human inspection such as low accuracy, poor real-time performance, subjectivity, and labor intensity. This paper describes the application of the Segment Anything Model (SAM) and Convolutional Neural Networks (CNN) to the analysis and image processing of workpieces produced on CNC machines to detect surface scratches and anomalies.*

Key words: image segmentation, instance segmentation, semantic segmentation, computer vision, work piece elements

1. INTRODUCTION

Modern production is based on CNC machines, and one of the most important tasks is ensuring high product quality (Wang *et al.*, 2018). However, the presence of anomalies or defects on these surfaces can lead to significant issues, such as reduced functionality, compromised structural integrity, and increased product failure rates. Traditionally, surface inspection in manufacturing settings has relied heavily on manual labor, human visual inspection, and conventional non-destructive testing (NDT) techniques. While these methods have served their purpose, they are often time-consuming, labor-intensive, and prone to human error. With the rapid advancement of artificial intelligence (AI) and computer vision, these techniques are increasingly being used for surface anomaly detection (Tao *et al.*, 2018).
Autonomous Workpiece Surface Anomaly Detection (ASAD) is an innovative approach that utilizes artificial intelligence (AI) and machine learning techniques to autonomously detect and classify anomalies or defects on the surfaces of workpieces in manufacturing processes (Saberironaghi, Ren and El-Gindy, 2023). ASAD aims to enhance the efficiency, accuracy, and reliability of surface inspection, ultimately improving product quality and reducing costs associated with manual labor and rework. Object detection algorithms can operate in real-time, enabling ASAD to detect and classify anomalies as workpieces move along the production line. This ensures prompt identification and immediate corrective actions, minimizing the impact of faulty workpieces on subsequent manufacturing processes.
This study explores the use of the Segment Anything Model (SAM) (Kirillov *et al.*, 2023) and Convolutional Neural Networks (CNN) for the analysis and image processing of workpieces produced on CNC machines to detect surface scratches and other anomalies (Medojevic and Ilic, 2023).

2. METHODS

The analysis of the quality of the workpieces begins after the completion of the CNC milling/turning process. The workpiece is transported to the quality control area and placed on rotating rollers (Fig 1.), two cameras that record the object being analyzed from above and from the side as it rotates. The cameras are based on a 5-megapixel OV5647 sensor, with adjustable focal length, 1/4" CCD size, 2.0 aperture, 6mm focal length, and 60.6° (diagonal) viewing angle. Moreover, the best sensor resolution is 1080p.

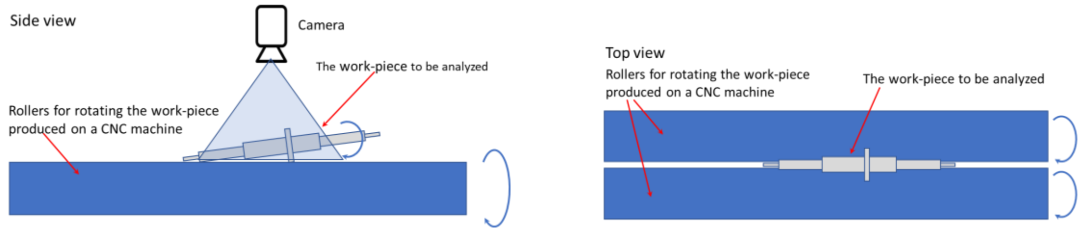

Figure 1: Quality control area with rollers

An overview of the workpiece anomaly detection system is presented in Fig. 2. The segment anything model (SAM) is capable of zero-shot generalization, so it can be used for the segmentation of objects in images without initial training (Kirillov *et al.*, 2023). The SAM model can analyze images from a wide range of areas, including biomedical, agricultural, and autonomous driving, as well as objects manufactured on CNC machines.

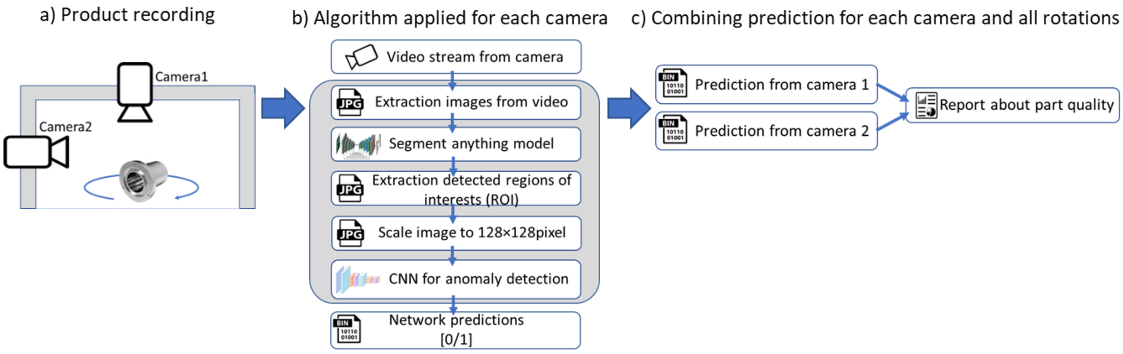

Figure 2: Overview of system for detection of work piece anomalies

Based on the bounding boxes detected using the SAM model, parts of the image are selected, which are then cropped and scaled to a standard size and then sent to a **convolutional network (CNN)** that is used to detect anomalies on the surface of the workpiece. The SAM model can be used to detect the position of complete workpieces, but also in the case of analyzing more complex workpieces consisting of several parts, the SAM model can determine the positions of each of the segments that would be individually cropped (see Fig 3) and then sent to the CNN network for anomaly detection.
The size to which the cropped image will be scaled depends on the type of element being analyzed, as well as whether we are analyzing the complete element or individual segments of the workpiece. If the complete working element is analyzed using a convolutional network, the cropped image is scaled to the dimension 512×512, but if we decide to analyze the segments of the workpieces individually, then we can scale each segment to a smaller dimension of 128×128.
CNN is a type of neural network commonly used for image and video processing tasks. The image to be processed is fed to the input layer of the convolutional network. The CNN network model used for the detection of anomalies on the product surface is located on the input layer of the expected image with dimensions of 512×512 pixels (complete workpieces) or 128×128 pixels (segments of workpieces). After the input layer, there are several convolutional and pooling layers, followed by a pair of fully connected layers. At the output of this convolutional network, one value is obtained, where the value 1 indicates the correct product, and 0 indicates incorrect products.
The dataset for training the CNN networks is generated by selecting a few good products, and as many damaged products as possible with scratches and other surface anomalies that need to be identified. Each of these products is then placed on a rotating platform and recorded using two cameras. In this way, several hundred images from different angles are collected for each product. When labeling images of correct products, all selected images can be automatically assigned label 1, which indicates that the image shows a defective product. However, when labeling an image of defective products, it may happen that damage is visible on some parts of the product, pictures where such damage is visible are given a label of 0. However, when labeling images of defective products, depending on the recording angle of such a damaged product, it may only be visible from some angles and not from others. If damage is visible

on the extracted images of such a working element, label 0 is assigned, and if the damage is not visible, label 1 is assigned. To automate the labeling process as much as possible and reduce the time for manual labeling, an active learning procedure can be applied to identify inconsistencies in data labeling in the dataset (Ilić and Tadić, 2022).
The cameras are connected to the Raspberry Pi Compute Module 4 (RPI CM4) I/O board, which runs algorithms based on machine learning. CM4 is a System on Module (SoM) that includes a CPU, memory, eMMC Flash, and power circuits. The module enables the utilization of the hardware and software stack in customized systems and form factors. Individual frames are taken from the video stream, and each frame is processed using the segment anything model to determine the bounding boxes.

3. RESULTS

Figure 3 shows a) an image of one of the workpieces produced on a CNC machine b), and c) an image generated by the SAM model where all the detected segmentation masks on which the detected segments of the workpiece can be seen are shown in different colors, and image d) they can be seen bounding boxes around the detected segments of the workpiece.

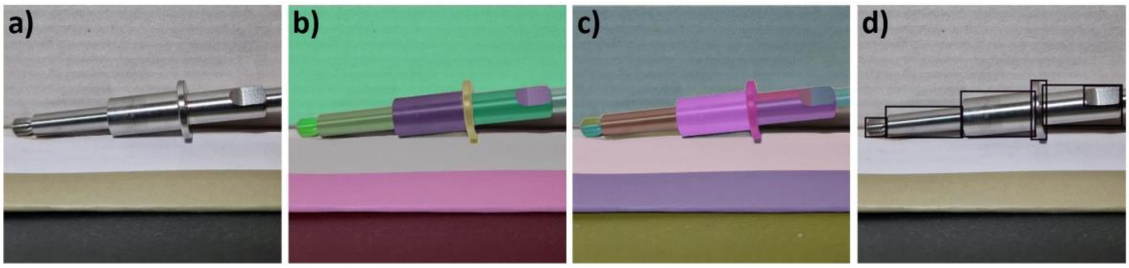

Figure 3: a) Original image of workpiece produced on CNC machine, b,c) Image processed with the SAM model, d) bounding boxes around the detected segments of the workpiece.

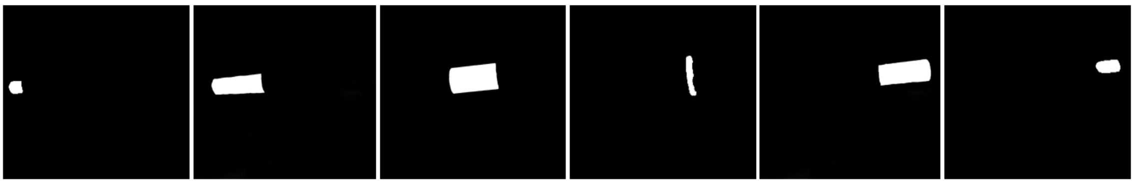

Figure 4: Segmentation masks generated by the SAM model

Figure 4 shows some of the segmentation masks of detected workpiece segments.
This project is still in the development phase, the CNN anomaly detection network was tested on a preliminary dataset that was generated based on available workpieces that were recorded while rotating on rollers in the control area. More than 15,000 images were extracted from such videos. The dataset was then split into 80% for training and 20% for testing. The accuracy of detection of anomalies and scratches on extracted images is 91.3%.

4. DISCUSSION

In this approach, objects are rotated on rollers and individual images are extracted from the video stream, resulting in recordings from multiple angles, allowing the machine learning model to detect scratches on workpieces from the angle of recording where the scratches are most visible. The product to be analyzed is placed on rotating rollers, while the process is video recorded with a 15 images per second frequency, so that in a few seconds, several hundred images of one product taken from several angles can be obtained. The developed software solution is primarily intended to detect surface scratches by gripping machine tools and classify results into two categories - products without surface scratches, and products with scratches. As work piece elements produced on CNC machines have highly reflective surfaces, so scratches are not easily noticeable, each of the images extracted in this way is analyzed by a convolutional network. Since there are a large number of images of the same object, if the scratches are not detected from some angle, it is enough to detect them from the angle from which they are most noticeable. As the paper reflects early project development stage, the provided approach still hasn't been tested in relevant environment, and the preliminary results obtained, still need to be validated via practical deployment.

5. CONCLUSIONS

The presented approach for autonomous detection anomaly on workpiece surface offers significant benefits over manual checking, including increased efficiency, enhanced accuracy, comprehensive coverage, cost savings, data-driven insights, and scalability. By leveraging AI and machine learning technologies, ASAD revolutionizes surface anomaly detection in manufacturing, enabling improved quality control and increased productivity.

Similar environments for ASAD can be easily scaled up or adapted to different manufacturing settings, product types, or surface materials. It can accommodate variations in workpiece sizes, shapes, or surface textures, making it suitable for a wide range of manufacturing types. Such environments are suitable to integrate ASAD into existing production lines or quality control systems, due to efficient implementation and deployment.

6. REFERENCES

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