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Integrating Image Processing Techniques in the Faster R-CNN Model to Detect Errors in Mechanical Details

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Abstract: Machine Learning and Computer Vision are increasingly being applied in detecting product defects across various industries such as industrial and agricultural, leading to increased efficiency, accuracy, and reduced labor costs. In this study, we utilized image processing algorithms with OpenCV library, combined with deep learning model FASTER R-CNN to identify bearing faults. Unlike previous studies that mainly focused on measuring box-shaped objects or only identifying the outer radius of an object, our study emphasizes identifying the radii of bearings along with a deviation of 0.02 mm. The porposed FASTER R-CNN model to accurately identify faulty bearings with a precision of 98%. Through our research and experimentation, we have also found that the CNN model is more accurate in detection than other models such as YOLO and SSD.

Keywords: *OpenCV, computer vision, mechanical product details, convolutional neural networks (CNN)*

1. Introduction

One production line in an hour can continuously produce hundreds or thousands of products depending on the type. However, every finished product is not 100% perfect and there will definitely be defective products. The final check before packing the product into the box is usually done by workers, so it will be very time consuming and inaccurate. Therefore, in order to save and increase accuracy, in recent years many manufacturing factories have applied machine vision technology to solve this problem.

Due to high practical demand, many researches and production processes of machine manufacturing technology companies have integrated image processing technology (some called non-contact measurement) in production process. For example, it is used for measuring small parts [6], identifying railway track defects (such as tie plates, dowels, anchors and bolts, defect identification, level analysis). Severity of defects and time condition analysis as well as long-term predictive assessment) [4], identification of pavement structural failures, safety checks for high-rise structures, visual Collected from the UAV [5], checked the pipe quality, laser streaks appeared on the inner surface of the pipe revealing the shape of the pipe. The 3D shape of the pipeline can be reconstructed considering the movement of the mobile robot along the pipeline [11].

Currently, many applications using machine vision technology have been developed in the agricultural fields, such as land-based and aerial remote sensing for natural areas for accurate crop resource assessment, postharvest quality and safety, detection, sorting and sorting, and process automation. This is possible because the machine vision system not only recognizes the size, shape, color and texture of the objects, but also analyzes and evaluates the attribute values of the objects or scenes. taken [7]. Image processing technology and AI are also applied in the medical field, diagnosing diseases through images [12]. In industry, computer vision is applied in mechanical part fault detectors, conveyor belts [13], or automotive disc brake inspection systems [10]. These systems use Cognex cameras and barcode readers that are used to improve identification quality and reduce labor costs.

For the field of mechanical production (such as auxiliary factories producing components for cars, motorcycles, or manufacturing machines requiring high precision...), or in the field of machine manufacturing, In general assembly, mechanical parts such as bearings, screws, jig jigs, ... need to be quality checked on many parameters, in which the determination of size and surface defects are common. and the most important. The object of study in this paper is ball bearings, as this is an important mechanical detail in many industrial applications. They are used to reduce friction and provide rotational support for rotating shafts in various machines and equipment. In order to ensure the quality of circular bearings before being put on the market, the quality control process normally goes through many steps such as checking material, wear, lubrication, load, durability.... In particular, there is a stage of checking the size and shape, specifically, round bearings must comply with the specified specifications, including diameter, shape accuracy, surface....

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Fig. 1. Mechanical product surface fault detection machine running on conveyor

Type 1: Normal

Type 2: Ball cap not closed error

Type 3: Scratches/Chatches of Edges

Type 4: Ball cap concave error

Fig. 2. Pictures of bearings and some basic faults

Specific research objectives of the article: Develop an image analysis solution to classify bearing products into 2 categories pass and fail; specifically as follows:

(1) Regarding the size, the requirements to measure the size of the upper and lower two sides need to ensure the following requirements:

- Inner diameter: 8mm standard size, ±0.02mm tolerance required, double check top and bottom.

- Outer diameter: 24 mm standard size, ±0.02 mm tolerance required, double check top and bottom.

(2) Surface defect, the product fails when it encounters one of the defects as described in Figure 2.

2. Building and Designing System

2.1. Proposing the plan

Stemming from the above objectives, the article proposes the technological diagram of the defective product identification system as Figure 3.

2.1.1. Principle of operation

First, the product from the container is fed into the product hierarchy (1). The product is pushed into the size inspection area (2) and checks for product surface defects (3) by a camera cluster (5) consisting of 02 cameras that check the top and bottom of the product, respectively: this stage checks error in size inside diameter, outside diameter and surface defects of the product. To ensure good image quality, a background lighting system (6) is required. After going through two testing stages (2 and 3), the data processing software automatically uses a combination of image processing technology and computer AI (7) to give the classification results as: pass and fail. The entire execution process is displayed on the monitor screen interface (9), the results are transmitted to the central controller (8) to control the actuators (4) to push the product out. outside the conveyor.

2.1.2. Select Camera

Here to ensure that the bearing size measurement results have an error of 0.02mm and have good image quality for easy image processing, we use Camera with 4K resolution (3840×2748), it is recommended to choose Camera OPT-CM1000-GL-04 used in Sampling block as Figure 4.

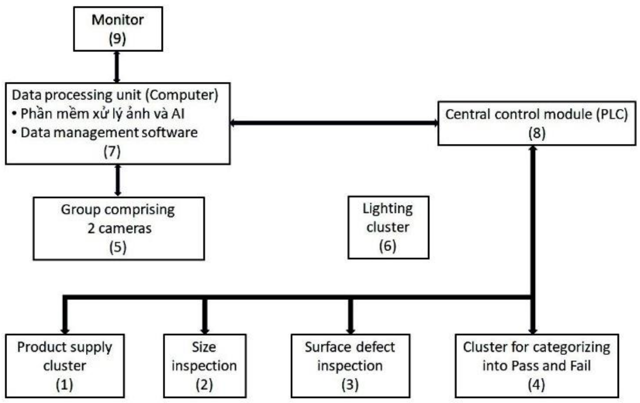

Fig. 3. Block diagram of automatic fault identification and classification system

Fig. 4. Camera OPT-CM1000-GL-04

Table 1. Camera parameters OPT-CM1000-GL-04

Resolution	3840×2748
Pixel area (μm^2)	0.185 x 0.185
Sensor Type	CMOS Rolling
Sensor	MT9J003
Frame rate (FPS)	9
Communication type	Ethernet
Shooting time	143μs-1s
Photo color	Mono

The next content of the article will introduce software to measure the size and identify surface defects… using OpenCV library and Faster R-CNN model.

2.2. Build a program to identify bearings fault

2.2.1. Method of determining the size

Studies [6, 7] have shown a method of measuring the size of objects based on the smallest rectangle surrounding the object, and measuring only the outermost size of the object. Previous studies applied image processing to determine the size of mainly box shapes, or only measured the outer radius parameter, but not yet applied to complex mechanical objects, such as bearings. On the basis of previous studies, we propose a method to determine the radii of mechanical bearings and use the method of the smallest circle around the object, as well as determine through binary points image.

To perform the measurement of radius, distance-related data in the article, it is necessary to use OpenCV, a Python library to support measuring dimensions and distances. In this study, we used the reference method. This method is implemented as follows: First, we select a standard object of known size called "reference object". This standard object has a shape similar to the shape of the object to be measured in terms of shape and texture to make it easier to calculate. The reference object used in the study took the form of a top-down ball bearing with a measured radius of $R = 24,000\ mm$. The next step is to capture the reference object at a given fixed height $h = 18\ cm$, with sufficient light intensity. Then, using the object separation algorithm, determine the radius of the reference object to be $Rc = 769$ px(pixel), deduce the true size of 1 pixel $24,000/769\,mm$ (so called the scale factor mm/px). To deal with the correct determination of bearing radii, we have processed the process as follows as Figure 5.

In this study, converting images from BGR color space to gray space using cv2.cvtColor function (image, cv2.COLOR_BGR2GRAY) to reduce image size and computational process. Gauss filter, cv2.GaussianBlur() function helps to blur the image, remove noise on the image. along with that blurring the redundant details Apply the Canny filter to detect the solid edge of the object in the image using the cv2.Canny() function. The contours of the object are found using the cv2.findContours() function. After having contours, filter the contours to find the largest contour and select that contour to determine the object size. From that contour, determine the bearing center and calculate the radii. Next, calculate the size of the object in the image based on the mm-to-pixel ratio, the P number (rate). Display the results or save the results to a file for later use. Finally, take a picture, multiply the radius measured in pixel units with the number P to get the true size of the object.

2.2.2. Surface fault identification method

The results in [10] have shown that the accuracy of Faster R-CNN is higher than that of other models. Through the above research process, the authors found that YOLOv3, YOLOv4, or SSD models have fast processing speeds. However, those models are not as accurate as the Faster R-CNN model. Along with that, Faster R-CNN demonstrates the ability to detect objects in dark light conditions, and small details are superior to the rest of the models. Therefore, we choose the Faster R-CNN model for detecting faults with small sizes of bearings.

The Faster R-CNN model works by using a CNN network to extract features from the input image, then using algorithms to search for regions that are likely to contain objects in the image. These regions are then fed into a classification layer to determine the object type and a regression layer to determine the exact location of the bounding box around the object.

Compared with previous studies: [2], [13], [18], [19], [20], [21], the studies have not used the Faster R-CNN model, mainly using the method. Deep learning methods and algorithms such as SVM, ANN, k-NN and unmodeled, or using simpler models such as CNN, or using less accurate models such as YOLO, or using round frequency image determination methods vibration ball on Mathlab. Therefore, this study shows an accurate method of surface fault recognition at the modeling level. Along with that, with previous studies mainly on Mathlab platform, or not under framework or modeling library, this study used Faster R-CNN model on Pytorch library.

The application of Faster R-CNN model to determine surface defects of mechanical products includes the following parts as Figure 6.

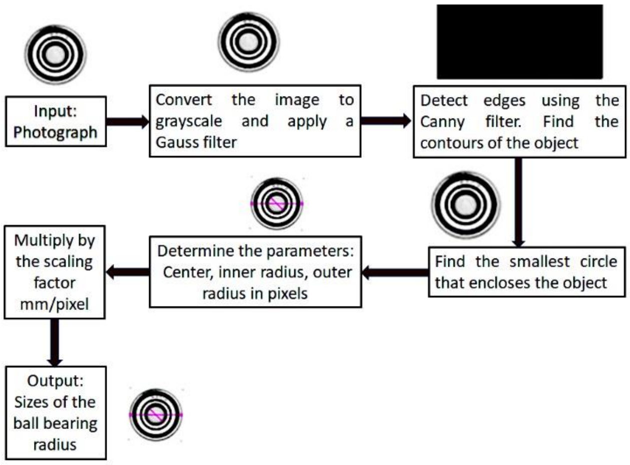

Fig. 5. Image processing for bearing size determination

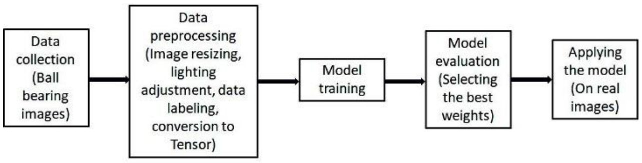

Fig. 6. Image processing for bearing size determination

First, we proceeded to collect images of the bearings from various angles. After that, we conduct data preprocessing using specialized pages: roboflow.com to process the image to the standard input size of 916x916, adjust the lighting,... and create an 8: ratio dataset: 2 for train and val, with the labels: "OK" for pass product, "NG-1" for unclosed failure, "NG-2" for lid reverse failure, "NG-3" for concave failure and " NG-4" with scratches.

Next, these images are fed into the Faster R-CNN network model to train and test the results. The model automatically detects surface features of the mechanical part, such as holes, cracks, and scratches, and marks them as defects. When a fault is detected, the model automatically makes a conclusion about the product's condition, thereby making the maintenance and repair process easier and more efficient.

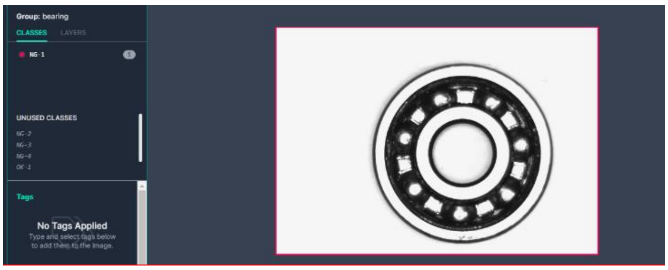

Fig. 7. Image during labeling

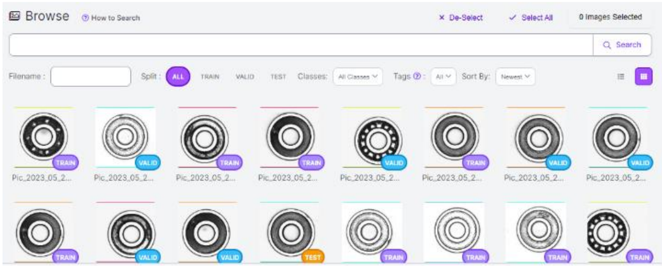

Fig. 8. Image after processing, labeling

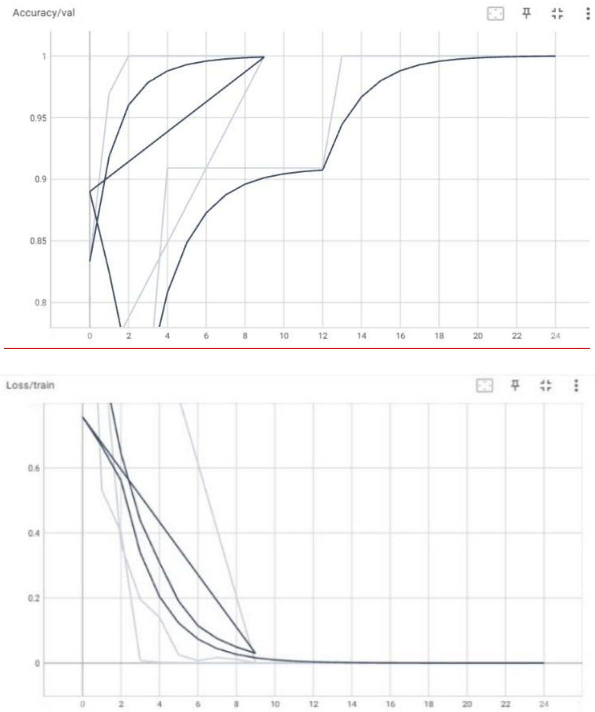

Fig. 9. Graph to evaluate the accuracy of the Faster R-CNN model training process on the ResNet101 backbone

3. Research Results

3.1. Result of object size determination

Result of accurate object size determination with error. This result shows the potential of applying image processing technology in industrial applications to improve product quality and reduce errors in the production process, see as Figure 10.

In addition, the measured result also depends on the distance from the camera to the bearing, temporarily called h, which is listed in the following table 2.

From the above data, the relationship function between the distance from the camera to the bearing, denoted as h, with the scale factor mm/pixel is obtained using the Lagrange method:

$$L(x) = \frac{-1}{840}h^4 + \frac{19}{420}h^3 - \frac{13}{140}h^2 + \frac{1883}{210}h - \frac{3191}{420}$$

where: $L(x)$ is the scale factor mm/pixel ; h is the distance from the camera to the bearing.

3.2. Surface fault identification results

The object identification results for the research with the object are bearings show that the Faster R-CNN network model can accurately identify the detailed faults on the bearings. Faults such as cracks, scratches, and dimensional deviations are accurately detected and classified.

Table 2. Data for a number of measurements with different heights h

Actual outer radius: 16.002 mm	h=13 cm	h=15 cm	h=18 cm	h=20 cm	h=23 cm
Outer radius measured in pixels:	929	916	769	676	568
Scale factor mm/ px	0.017	0.017	0.021	0.024	0.028

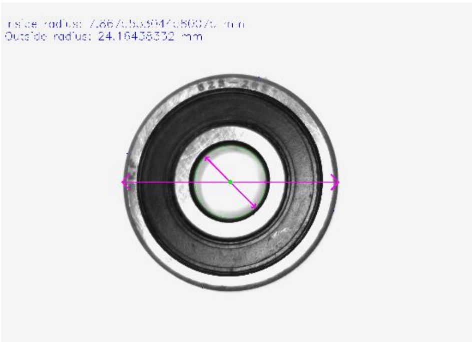

Fig. 10. Dimensional results

Table 3. Surface fault detection results with different network architectures

Faster R-CNN model and backbones	Accuracy	Training cycle length (on GPU)
ResNet 50	90%	2 hour
ResNet101	92%	3 hour
VGG16	86%	1 hour 30 minutes
VGG19	87%	2 hour
EfficientNet-B0	91%	2 hour 30 minutes

This shows that the most accurate backbone is ResNet101 in diagnosing mechanical product details.

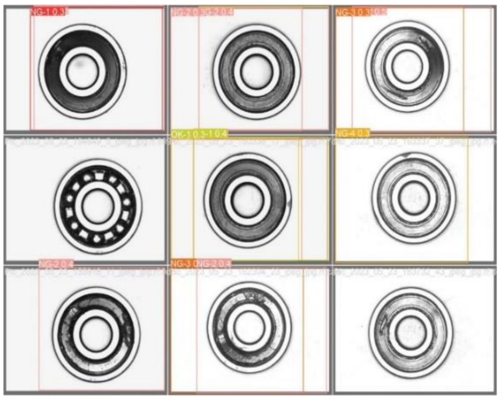

Fig. 11. Surface defect detection results

3.3. Result of building test model

Introducing some pictures of experimental models Fig 12; 13 and 14:

Fig. 12. Model overview image

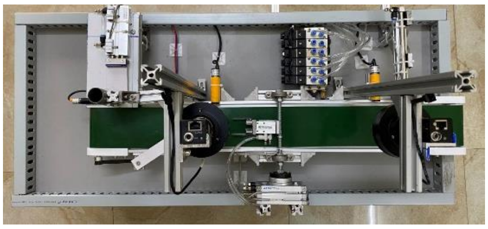

Fig. 13. Model image from above

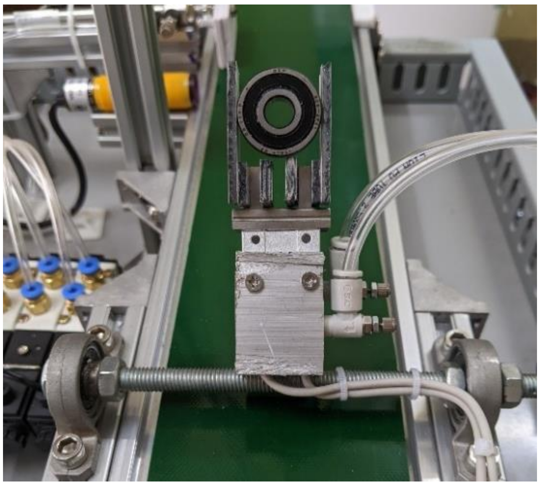

Fig. 14. Active Flip Cluster

Fig. 15. Monitoring interface on the computer

The Monitoring block uses Microsoft Visual Studio software to design the control interface on Winform – C#. The Image Processing block uses the OpenCV library in the Python programming language, see as Figure 15.

4. Conclusion

The research paper introduced the application of image processing and artificial intelligence in the fault diagnosis system of mechanical product details. Using convolutional neural networks (CNN) and image processing techniques, we have succeeded in detecting and classifying surface defects such as scratched, ungrounded, damaged, and at the same time determining the product dimensions. The method is implemented in Python programming language, achieving positive results and showing potential for practical applications.

Based on the research results, we make the following recommendations:

- Continue to research and develop methods to improve model performance, especially in detecting surface defects with high similarity or small size;

- Extend the application of the method to other types of mechanical products, not just limited to the mechanical details studied in the paper;

- Collaborate with manufacturers and mechanical industry experts to understand actual needs, adjust and improve models to suit each specific product type and production environment.

By applying the above recommendations, we believe that the system of fault diagnosis and mechanical product sizing using artificial intelligence and image processing will continue to be developed and widely applied in industrial applications. manufacturing and product quality control. This will help improve efficiency and accuracy in the manufacturing process, while minimizing product errors, and enhancing the reliability and reputation of the manufacturer.

In this conclusion, we hope that our research paper will highlight the potential of CNN network model and image processing in solving real-life problems and encourage researchers, entrepreneurs, Industry and government invest in the research and application of these technologies.

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