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Surface Defects Detection on Metallic Objects

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Abstract*— *Inspection of metallic parts is a challenging task and has demands in a variety of manufacturing quality control applications. Computer visions are typically used for the purpose of inspection, in particular, for detection, recognition, and classification of surface features representing manufacturing imperfections. This research focuses on automating the process of defects detection using Computer Vision (CV) and Machine Learning (ML) algorithms. The objective of this research is bifold: 1) programming a robotic arm for capturing multiple images of the object and 2) developing CV and ML algorithms for detecting and classifying defects. This paper discusses different types of surface defects on metallic objects. This paper also compares the performance of EfficientDet and a ResNet neural networks model for surface defects detection.

Keywords: surface defects, computer vision algorithms, defects detection, deep learning, EfficientDet.

I. INTRODUCTION

Surface defect detection has always been a crucial part of metal manufacturing process. Due to the chemical and physical properties of some metals and the manufacturing process, the surface defects are almost impossible to avoid. These defects could be cosmetic issues, but they could also affect the corrosion and wear resistance of the metal parts. In addition to that, by catching the defect earlier, the manufacturer can adjust the production process to avoid the spread of defects to the whole batch. For a long time, people supervising the production line were the only means of defect inspection; however, this type of supervision may not be the best option due to many factors. In recent years, with the advancements in Machine Learning and Computer Vision, computers are a great help in this area.

In industrial manufacturing, the quality of products is one of the most important factors of production. Visual inspection is the key technology of products quality. Visual Inspection systems had been introduced into production lines in 1970s [2]. One of the early applications was the aluminum spattering inspection on semiconductor pellets at the middle of 1970s. There are two aims to execute visual inspections in production lines. First one is to monitor production lines to keep the lines in good condition, and the second is to evaluate the products if they keep the quality as the final products. Most of the early visual inspection systems had been developed from the first viewpoint. As the second view point, the inspection system should evaluate products from the user's viewpoints. It means that the visual inspections should have the human feelings. Today, visual inspection is going to be applied to the human impression evaluation, such as the beauty of products, small and vague defects on products, etc. In these cases, it is very important to evaluate the human sensitivity of defects.

Auto inspection process using robotic arm aims to mimic a real-life manufactory to screen defective and non-defective materials. The robot project, which consists of five components: Materials, Conveyor belt, Infrared Sensor, Robotic Arm, and Camera (Fig.5), implemented Blockly to control the robotic arm, allowing the robotic arm to accomplish the task that the user requested. The complete flow chart of robot operation has been rendered in Figure 2.

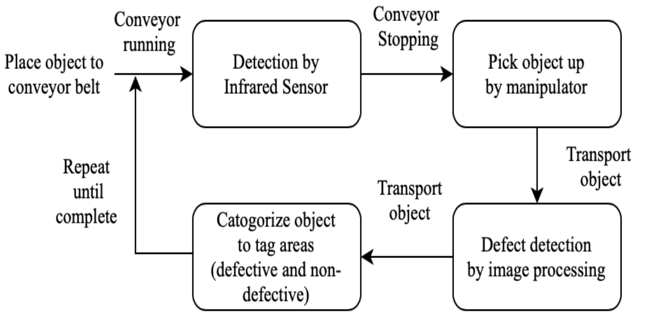

Figure 1: Auto Inspection Process

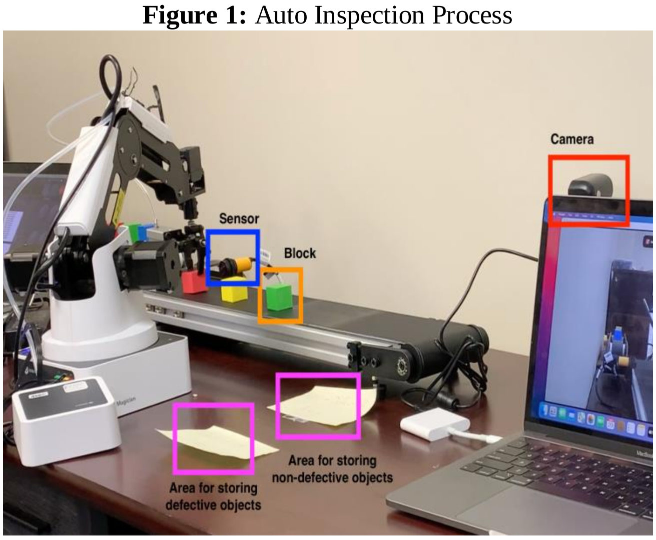

Figure 2: Typical Auto Inspection System

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II. LITERATURE OVERVIEW

Due to the metal manufacturing industry nature, it is difficult to obtain an adequate amount of data that can be used to train models because some defects occur scarcely. Convolutional Neural Networks (CNN) technique effectively used for defect detection in recent years could have a significant drop in performance because of data skewness. Some data augmentation techniques such as rotation, flipping, sharpening, blurring, etc., are straightforward approaches for enriching the data, but they can be ineffective. Thus, Yun, P.L. et al. [1] proposed using convolutional variational autoencoder (CVAE) to generate images for each defect. They focused on rolling still process defects. They proposed a deep learning algorithm based on convolutional neural networks(CNN) for automatically classifying defects.

Another approach for solving the data scarcity problem proposed by Li., R. [2] is to use Generative Adversarial Network (GAN) algorithmic architecture, which is successfully used to generate realistic-looking fake images almost identical to real photos. To solve the issue with the lack of large sets of images with metal surface defects Fu, J. et al [3] proposed to use deep learning network with transfer learning method: their algorithms first extract features of the metal surface image with the VGG16 extractor that was already trained on the images from imagenet, and then access CNN to train the classifier. Kovalenko, I. et al. [4] in their research considered 3 classes of defects: holes, grooves/scratches, and rolling defects since the number of defects in modern metal production is much smaller than in the past (GOST - Russian standards and regulations published in 1990, distinguish 64 rolled metal surfaces defects). They use ResNet to classify defects. While many approaches to detect and classify steel sheet defects use low-cost industrial cameras Didarul, A. and Shamim A. [5] in their article proposed to use a single image and segment it into regions for further classification. They used U-NET and Residual U-net for this approach. Using Convolutional Neural Networks improved with Pseudo-Label were proposed for steel surface defects recognition [6]. Pseudo-Label is a semi-supervised framework that allows to generate fake labels for unlabeled data, and thus fewer labeled samples are needed to train the model. However, the fact that this model uses semi-supervised learning, it has lower accuracy than supervised models. Transfer Learning has proven to be effective in detecting defects of metal cylindrical shells [7]. Truncated Inception-v3 NN was adopted as Deep Convolutional Neural Network and Logistic Regression was used as a binary classifier between defective and non-defective parts. The Inception-v3 NN was trained with 3.2 million images; it is “immune to illumination and could extract features which are invariant to colors” [7].

Tao, X., et al. [8] in their research on metallic surfaces defects detection and classification utilized Cascaded Autoencoder (CASAE), which transforms image with defects into a pixel-wise prediction mask obtained by semantic segmentation. After the image passes the threshold model, a compact convolutional neural network is used to classify defects. The limitation for this method is that CNN requires a labeled dataset. In the article [9], Chu, M., et al., propose to use twin Support Vector Machines (SVM) with multi-information (MTSVMs) for defects classification on metal surfaces. As preprocessing they use Median and bilateral filters, as well as Watershed Algorithm for defect segmentation. They were able to achieve an accuracy of more than 94% on the dataset with noisy samples. However, though SVM shows good results, it is a slow algorithm, which might be a problem in production environments. In [10], Wang, H., et al., used a matching (guidance) template generated from multiple defect-free images to detect if there is a defect on a surface. They used a sorting operation to sort gray levels within each column of image, and then subtract the template image. A review article [11] summarizes various methods applied for metal surfaces inspections. It was reported that the most used model for metal surface defects before 2010 was back propagation Neural Networks, but after 2010 SVM was widely used.

III. DATASETS & TYPES OF DEFECTS

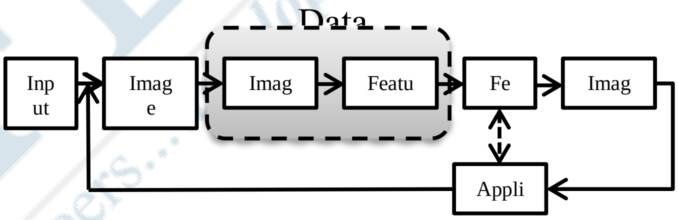

Figure-3: Image Analysis Process

The metallic defects dataset is crucial for detection. It should have different angles and positions for each defect, allowing the system to fully recognize the defect. For our research, we have collected various images of metallic defects. Depending on the defect features, We classify metallic defects into five types: Crack, Spot, Edge, Scratch, and Pinhole. Crack includes Crazing, Inclusion, Pitted Surface, Rolled in scale, and Welding line. All of them have a common feature, which is visible and tactile irregularly or discontinuously line or spot on the surface. The spot includes Patches, Water Spot, Oil Spot, and Silk Spot. Their common feature is a visible mark on their surface but not tactile. The mark differs in color or texture from the surface around it. Edge includes Crescent gap, whose feature is the edge happen discontinuity on the object edge considering it as edge defect. Scratch includes Crease, Waist Folding, and Scratch. Their common feature is that a thin line on the surface looks like an abrasion mark. They are visible, but they can be either tactile or not tactile. Pinhole includes Punching and Rolled pit. Their noticeable feature is a small hole or strip-like roll pit on the object's surface. (Defects Collection Below)

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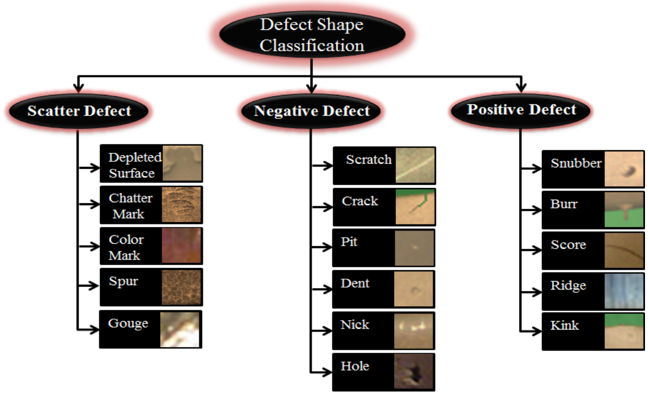
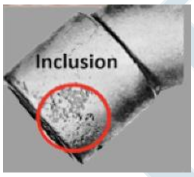
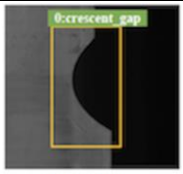
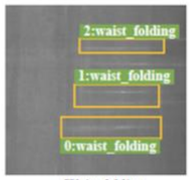


Figure-4: Defect Shape Classification

Table-1: Common Defect Types and Description

Type of Defect	Description	Image of Defect
Crazing	Crazing is the phenomenon that produces some cracks on the surface of a material.	
Inclusion	Small spot, strip shape and block irregularly distribute in the surface	
Pitted surface	It is kind of corrosion range of metal surfaces and penetrates into the metal interior.	
Rolled in scale	A rolled-in scale defect occurs when the mill scale is rolled into the metal during the rolling process.	
Welding line	weld surface irregularities, discontinuities, imperfections or inconsistencies that occur in welded parts.	
Spot		
Patches	A part of metal marked out from the rest by a particular characteristic.	
Water Spot	A water spot is produced by drying in production. It is similar with other defects such as oil spots.	
Silk Spot	A local or continuous wave-like plaque on a strip surface.	
Oil Spot	Oil spot is usually caused by the contamination of mechanical lubricant	
Edge		
Crescent gap	Cutting somethings results in defects, like half a circle.	 Crescent gap
Scratch		
Crease	A crease is a vertical transverse fold, with regular or irregular	
Waist folding	There are obvious folds in the defect parts, a little like wrinkles.	 Waist folding
Scratch	A scratch is a mark of abrasion on a surface.	

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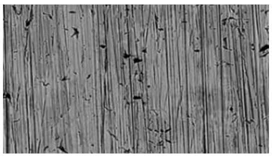
Pinhole		
Punching	Mechanical failure may lead to unwanted punching (hole).	
Rolled pit	Rolled pits are periodic bulges or pits are punctate, flaky, or strip-like on the surface.	

IV. DEFECTS DETECTION MODELS

For detection, We applied OpenCV for detecting defects. (1) Grayscale (reduce noise on the object surface). (2) Gaussian Filter (blur the image, allowing the image to show more detail at the edge of the object). (3) Canny (allows images to show all edges between two threshold values (min and max values)). It means between min pixel value and max value being white line, others being black. (4) we used the Contours function, where we used FindContour to find out all of the contour and area. Based on the limited area, we used drawContour to draw the contour based on the area. Then, we used Approx to point out all edge points based on the contour area.

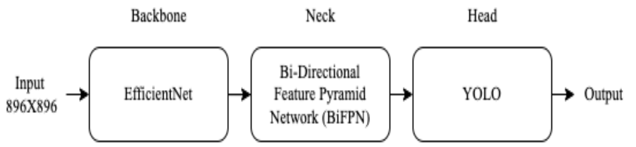


Figure 5: Model Architecture

V. RESULTS AND ANALYSIS

For testing the algorithms, we used two different types of dataset. The first dataset was downloaded from NEU Metal Surface Defects Databse which contains six kinds of typical surface defects of the hot-rolled steel strip are collected, i.e., rolled-in scale (RS), patches (Pa), crazing (Cr), pitted surface (PS), inclusion (In) and scratches (Sc). The database includes 1,800 grayscale images: 300 samples each of six different kinds of typical surface defects. But for this analysis, the dataset divided into 3 directories. The training directory contains 276 images of each class from the 300 images. The rest 24 images of each class also divided into tests and valid datasets. We developed a model using EfficientNetB0 from Tensorflow keras model and applied on dataset-1. EfficientNet-b0 is a convolutional neural network that is trained on more than a million images from the ImageNet database. The total number of layers in EfficientNet-B0 the total is 237

For the second dataset, we collected and manually annotated 94 images with 327 scratches, 257 dents, 335 paint and 154 glue marks to train a model. Sample images and defect distribution in the dataset are presented in Figure 6a and 6b. Having limited number of images, we utilize transfer learning - fine-tuning of a pre-trained network - effective in defect detection and classification [1, 2]. We explored several architectures and chose EfficientDet D3 model [3] because of good trade-off between speed and performance. The model combines EfficientNet, Feature Pyramid Network, and YOLO architectures. Input has high resolution, 896X896, which allows the model to detect fine defects.

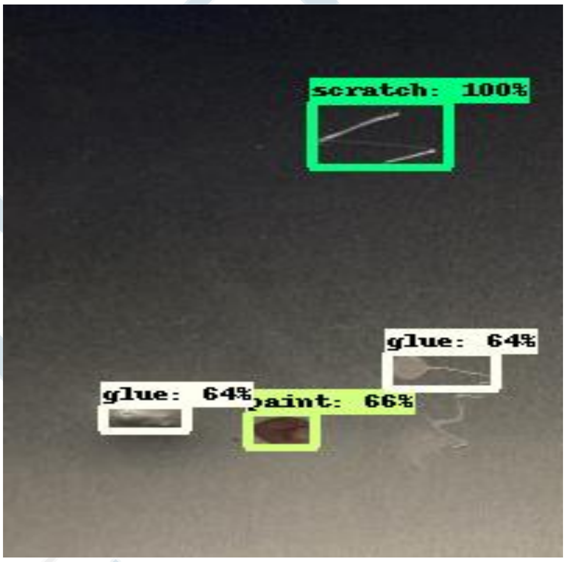


Figure 6a: defects on metallic sheet

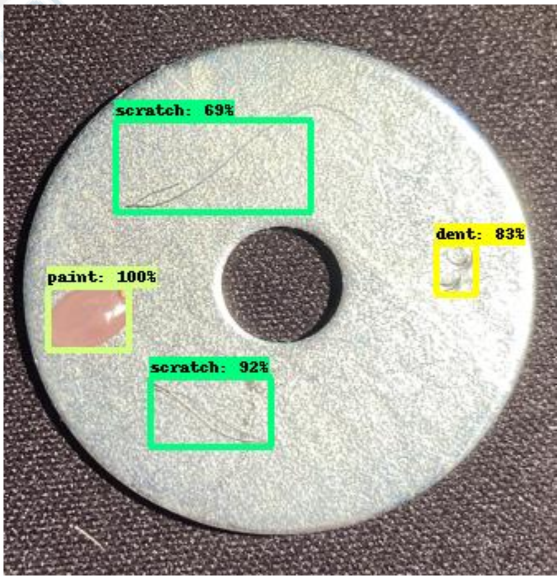


Figure 6b: defects on a washer

Trained object detection model to detect and classify metallic surface defects. The sample output bounding boxes and scores of the model are presented in Fig. 6b. The mean average precision (mAP) scores for our and original models are shown below.

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Table-2: Results Comparison on Dataset-2

Model	mAP	mAP_{50}	mAP_{75}
EfficientNetB0	55.2	79.6	56.1
EfficientDet-D3	67.2	85.9	71.2

VI. CONCLUSIONS

When operating the robotic arm, the object and the robotic arm should be accurately positioned so that it can delicately pick up the object. We need to capture the coordinate where the object stops under the action of the sensor, which allows the robotic arm to move to this point. This coordinate is rigorous since the size of the object is almost the same as the clamp size of the manipulator, and if this coordinate is slightly off, the manipulator cannot pick up the object. Collecting relevant dataset was very challenging since there are not much datasets available online. So, we manually implanted defects and tested EfficientNetB0 and EfficientDet-D3. As seen in table-2, EfficientDet-D3 achieved promising results and if trained with more dataset, we believe that more accuracy can be achieved.

VII. ACKNOWLEDGMENTS

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REFERENCES

[1] Yun, P.L. et al., Automated defect inspection system for metal surfaces based on deep learning and data augmentation, Journal of Manufacturing Systems, Volume 55, April 2020, Pages 317-324, [Accessed 02/10/2021] https://doi.org/10.1016/j.jmsy.2020.03.009

[2] Li, R., Metal surface defect detection based on few defect datasets, AIP Conference Proceedings, Published Online: 09 December 2019, [Accessed 02/11/2021] https://doi-org.ezaccess.libraries.psu.edu/10.1063/1.5137871

[3] Fu. J. et al., Recognition of Surface Defects On Steel Sheet Using Transfer Learning, arXiv preprint arXiv:1909.03258, Published Online: 7 Sep 2019, [Accessed 02/18/2021] https://arxiv.org/abs/1909.03258

[4] Konovalenko, I., et al. Steel Surface Defect Classification Using Deep Residual Neural Network. Metals. 2020; 10(6):846. https://doi.org/10.3390/met10060846 https://www.mdpi.com/2075-4701/10/6/846#cite

[5] Didarul, A., Shamim, A. Deep Learning-Based Defect Detection System in Steel Sheet Surfaces. 10.1109/TENSYMP50017.2020.9230863. June 2020, [Accessed 03/11/2021]

[6] Gao, Y., et al. A Semi-Supervised Convolutional Neural Network-Based Method For Steel Surface Defect Recognition. Robotics and Computer-Integrated Manufacturing. February 2020. https://doi.org/10.1016/j.rcim.2019.101825

[7] Gong, Y., et al. Automatic Defect Detection for Small Metal Cylindrical Shell Using Transfer Learning and Logistic Regression. Journal of Nondescriptive Evaluation. 18 February, 2020. https://doi.org/10.1007/s10921-020-0668-4

[8] Tao, X., et al. Automatic Metallic Surface Defect Detection and Recognition with Convolutional Neural Networks. Applied Sciences, 6 September 2018, 8(9) https://doi.org/10.3390/app8091575

[9] Chu, M., et al. Multi-class classification method using twin support vector machines with multi-information for steel surface defects. Chemometrics and Intelligent Laboratory Systems. 15 May 2018. Vol. 176. Pp. 108-118 https://doi.org/10.1016/j.chemolab.2018.03.014

[10] Wang, H., et al. A Simple Guidance Template-Based Defect Detection Method for Strip Steel Surfaces. IEEE Transactions on Industrial Informatics. 17 December 2018. 15(5). Pp. 2798 - 2809. DOI: 10.1109/TII.2018.2887145

[11] Sun, X., et al. Research Progress of Visual Inspection Technology of Steel Products—A Review. Applied Sciences. 8 November 2018. 8(11). https://doi.org/10.3390/app8112195