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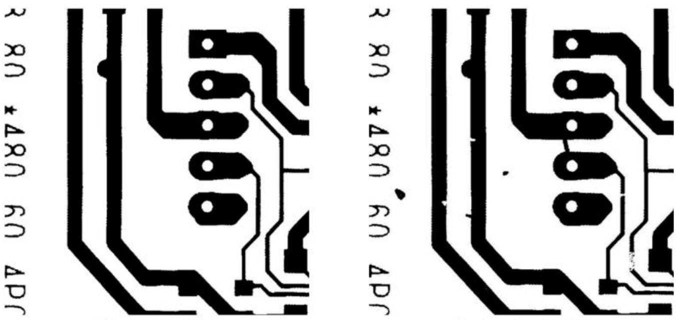
Part I: Technical Overview

Abstract

Quality control is an essential process in the industry to ensure that the products meet the required standards and specifications. Traditional quality control methods involve manual inspection, which is time-consuming, subjective, and prone to errors. Machine learning and computer vision techniques have revolutionized quality control in the industry by automating the inspection process, reducing the time required for inspection, and improving the accuracy and reliability of the inspection process. In this paper, we discuss three examples of using machine learning and computer vision in quality control: binary classification of defect vs non-defect, object detection.

Binary Classification of Defect vs Non-Defect

Binary classification is a fundamental problem in machine learning, and it has numerous applications in quality control. In the industry, binary classification is used to classify products into defect and non-defect categories. Machine learning algorithms are trained on a dataset of images of defective and non-defective products. The algorithm learns the features that distinguish between defective and non-defective products and uses these features to classify new products.



Normal PCB   Defective PCB

(A sample of dataset which contains normal and defective PCB [1])

One example of binary classification in quality control is the inspection of printed circuit boards (PCBs). PCBs are used in many electronic devices, and their quality is critical for the performance and reliability of the devices. Traditional inspection methods involve manual inspection of the PCBs, which is time-consuming and prone to errors. Machine learning and computer vision techniques have been used to automate the inspection of PCBs. A machine learning algorithm is trained on a dataset of images of defective and non-defective PCBs. The algorithm uses these images to learn the features that distinguish between defective and non-defective PCBs. The algorithm can then classify new PCBs as defective or non-defective with high accuracy and reliability.

Object Detection

Object detection is a computer vision technique that involves detecting and localizing objects within an image. Object detection has numerous applications in quality control, including defect detection and counting the number of objects in a given image. Machine learning algorithms are trained on a dataset of images that contain the object of interest, along with its location in the image. The algorithm learns to detect the object and localize it within the image.

Fig 1(Defected)

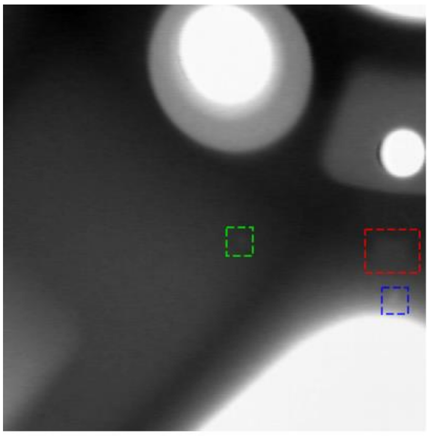


Fig 2(Defects annotated)

In this example, a machine learning algorithm is trained on the GDxray[2] dataset to detect and localize defects within the x-ray images of industrial components. The GDxray dataset is a publicly available dataset for object detection in industrial x-ray images. The dataset contains over 19,000 x-ray images of various objects, including electronics, automotive parts, and mechanical components. Object detection using the GDxray dataset has been used to automate the inspection of industrial components, improve production efficiency, and reduce the cost of quality control.

Using Normal and Ultrasound Images for Defect Detection*

In many industries, such as aerospace, automotive, and manufacturing, it is critical to detect defects in products before they lead to catastrophic failure or malfunction. Ultrasound imaging is a widely used non-destructive testing technique in industry for detecting defects in products. However, manual inspection of ultrasound images is time-consuming and prone to errors. Machine learning algorithms can be trained on normal and ultrasound images of products to automate defect detection and improve the efficiency and accuracy of quality control processes.

Rail defect detection is an essential task to ensure the safety and reliability of railway transportation. Traditional methods of rail defect detection include visual inspection and manual ultrasonic testing, which can be time-consuming and labor-intensive. In recent years, there has been growing interest in using computer vision and machine learning techniques to automate rail defect detection.

One promising approach is to combine camera Image and ultrasound B-scan images using data fusion techniques. Using multi-source data feature extraction and multi-scale feature fusion networks to detect the rail surface defect. [3]

* This is a theoratical example, due to limited access to training data and code repositories.

Part II: Organizational Overview

Agenda:

We want to organize the 45 minutes of the session as follows:

1. First 15 minutes as the introduction to:
    a. The project
    b. Topics to be covered
    c. Quick summary of the basics of machine learning/Python
2. Then next 30 minutes as:
    a. 10 minutes for a basic example (binary classification)
    b. 10 minutes for basic Object detection example
    c. 5 minutes for questions and answers

Target group:

The primary target group would be Students and young professionals from the industry. A working pre-knowledge of machine learning necessary (Also python) would be required. However, a very quick overview will be provided.

Number of participants:

The maximum number of participants allowed: 10. For better management and delivery of the contents of the workshop.

Workshop Goals:

1. Introduce audience to computer vision, deep learning and their challenges in Quality control.
2. To give insight into real world examples their working and limitations

Methodology:

1. The workshop will be conduct in python using Jupyter notebooks.
2. The examples would contain pre-trained models (less scope for hands on training) and pre-build notebooks **.

**Each participant would be required to have a laptop with python and Jupyter to be able to access the code.

Project goal -- KI-Lab DIANA:

The primary objective of the KI-Lab DIANA project is to equip Small and Medium-sized Enterprises (SMEs) with artificial intelligence. To achieve this goal, the project offers consultations and hands-on training tailored to the needs of SMEs. These consultations and trainings are specifically focused on the practical applications of artificial intelligence to help solve various real-world challenges. One of the most significant challenges faced by the industry is maintaining consistent quality over time while adhering to the required standards and specifications. In this workshop, we aim to provide an overview of the issues and challenges involved in handling real-world problems related to quality control. Our goal is to introduce participants at the conference to this topic and to provide them with a brief understanding of the subject.

Suggested literature:

1. Rene Y. Choi, Aaron S. Coyner, Jayashree Kalpathy-Cramer, Michael F. Chiang, J. Peter Campbell; Introduction to Machine Learning, Neural

Networks, and Deep Learning. **Trans. Vis. Sci. Tech.** 2020;9(2):14. doi: https://doi.org/10.1167/tvst.9.2.14.

2. Mahony, N. O., Campbell, S., Carvalho, A., Harapanahalli, S., Krpalkova, L., Riordan, D., & Walsh, J. (2019). Deep Learning vs. Traditional Computer Vision. *ArXiv*. https://doi.org/10.1007/978-3-030-17795-9

3. Javaid, M., Haleem, A., Singh, R. P., Rab, S., & Suman, R. (2022). Exploring impact and features of machine vision for progressive industry 4.0 culture. *Sensors International*, *3*, 100132. https://doi.org/10.1016/j.sintl.2021.100132

4. Bhatt D, Patel C, Talsania H, Patel J, Vaghela R, Pandya S, Modi K, Ghayvat H. CNN Variants for Computer Vision: History, Architecture, Application, Challenges and Future Scope. **Electronics**. 2021; 10(20):2470. https://doi.org/10.3390/electronics10202470

5. Leyendecker, L., Agarwal, S., Werner, T., Motz, M., Schmitt, R.H. (2023). A Study on Data Augmentation Techniques for Visual Defect Detection in Manufacturing. In: Lohweg, V. (eds) Bildverarbeitung in der Automation. Technologien für die intelligente Automation, vol 17. Springer Vieweg, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-66769-9_6

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[1] Tang, S., He, F., Huang, X., & Yang, J. (2019). Online PCB Defect Detector On A New PCB Defect Dataset. *ArXiv*. /abs/1902.0619

[2]: Riffo, Vladimir & Lobel, Hans & Mery, Domingo. (2015). GDXray: The Database of X-ray Images for Nondestructive Testing. Journal of Nondestructive Evaluation

[3] Z. Chen, Q. Wang, Q. He, T. Yu, M. Zhang and P. Wang, "CUFuse: Camera and Ultrasound Data Fusion for Rail Defect Detection," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 11, pp. 21971-21983, Nov. 2022, doi: 10.1109/TITS.2022.3189677.