Automated Metal Surface Defect Detection

Chi Wee Tan[1(✉)], Joren Mundane Antequisa Pacaldo[1], Wah Pheng Lee[1], Gloria Jennis Tan[2], Siaw Lang Wong[3], and Jun Kit Chaw[4]

[1] Faculty of Computing and Information Technology, Tunku Abdul Rahman University of Management and Technology, 53300 Setapak, Kuala Lumpur, Malaysia
chiwee@tarc.edu.my

[2] Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Cawangan Terengganu, 21080 Kuala Terengganu, Terengganu, Malaysia

[3] HELP International School, 40150 Shah Alam, Selangor, Malaysia

[4] Institute of IR4.0, Universiti Kebangsaan Malaysia (UKM), 43600 Bangi, Selangor, Malaysia

Abstract. Product defect detection is one of the essential steps in quality control to ensure product safety. Inspection needs to be conducted regardless of during or at the end of the manufacturing process to ensure all products complies with specification and requirements. In-process defect detection is conducted to identify any deviations or defects in the product to ensure all pieces are consistent and safe to use. However, manual quality inspection procedures are often time-consuming, expensive, and prone to errors especially for manufacturers that conduct large-scale production on a daily basis. Hence, many industries have started to leverage and incorporate technologies such as IoT devices, Computer Vision, Artificial Intelligence and Deep Learning in the manufacturing process for a more robust and efficient defect detection system. This project aims to identify the most suitable image segmentation method for patch defect and scratch defect respectively and accurately localize the patch defect on metal surfaces and evaluated using Intersection over Union (IoU). In this project, a total of 3 image segmentation methods are attempted namely threshold-based segmentation, edge-based segmentation and clustering techniques are implemented and compared for detecting patch and scratch defects. We successfully identified that the threshold-based segmentation method is more suitable for patch defects whereas the edge-based segmentation method is more suitable for scratch defects. Among the attempted threshold-based segmentation, namely simple thresholding, adaptive thresholding and Otsu's Binarization, we discovered that the best technique to detect patch defects is Otsu's Binarization.

Keywords: product defect · manufacturing · scratches · patches

1 Introduction

Computer vision has come a long way in terms of its capabilities, and it is being applied in manufacturing industry [1]. As one of the main raw materials of industrial products, metal will inevitably be damaged on its surface such as patches and scratches due to

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inappropriate process and storage. Most of the time, metal defects are visible on the surfaces. Patches are usually formed when unfinished metals are not properly and evenly coated. When this happens, moistures penetrate the coating and get locked under the finish, causing oxidation to occur. The oxidation of metal will possibly lead to rusting and corrosion, an irreversible damage to the metal surface if left untreated [2–4]. Besides, scratches are produced by friction or crushing of metal against other materials during the manufacturing process [5]. It could lower the product strength due to the disruption of the fixed metal molecule structure.

It is crucial to eliminate defective metals because of several reasons. Despite the fact that metal surfaces with patches and scratches are not suitable to be used on the outer appearance of certain products, the quality of the metal is the key concern. Patches and scratches both contribute to the shortening of metal durability. Scratches are also the possible signs of metal fatigue. The damage of the metal surface will seriously affect the quality and appearance of products, leading to serious consequences such as adverse industrial accidents.

However, in traditional manual inspection, there will be problems such as missed detection and low efficiency under the influence of human subjective factors. In this prototype, we propose a machine vision algorithm to facilitate this process. The key direction of this prototype is to develop an accurate and efficient automated metal surface defect detector to replace humans in performing visual inspection. The approach used in this prototype will be image segmentation, one of the popular image processing techniques. The following section will be arranged by Sect. 2 Literature Review, Sect. 3 Methodology and followed by Sect. 4 Result and Discussion. Last but not least, conclusion in Sect. 5.

1.1 Objectives

- To identify the most suitable image segmentation method for patch defect and scratch defect respectively
  Three image segmentation approaches including threshold-based segmentation, edge detection segmentation and clustering techniques. The threshold-based segmentation includes simple thresholding, adaptive thresholding and Otsu's Binarization while the edge detection segmentation methods comprise the Sobel, Laplacian and Canny edge detector. For clustering approach, K-means clustering is attempted. These segmentation approaches will be evaluated, and the best technique will be identified as the most suitable image segmentation method for patches and scratches defect detection respectively.
- To accurately localize the patch defect on metal surfaces
  There are a total of 18 metal surface images with patch defect type will be used to demonstrate the functionality of the system. As we proposed an algorithm that is capable of detecting defects on metal surfaces, we expect to see clear highlights and visualization of the patch defects in the tested images.
- To accurately localize the scratch defect on metal surfaces
  There are 19 metal surface images with scratch defect type will be used to demonstrate the functionality of the system. As we proposed an algorithm that is capable of

detecting defects on metal surfaces, we expect to see clear highlights and visualization of the scratch defects in the tested images.

1.2 Motivation

Automated Visual Inspection in Manufacturing Companies. Automated Visual Inspection is a form of quality control that includes analyzing and examining the production line. For human visual inspection, inspectors have to undergo special training to be equipped with professional knowledge and experience. However, there are many limitations to what humans can achieve. For instance, humans are prone to errors and mistakes which arise from several issues such as fatigue and lack of attention. However, this problem is non-existent and could be overcome with machines and computers. Besides, with the improvements and development of such advanced inspection systems, detection of defects that are hard to be noticed by the human naked eye are made possible. By implementing automotive quality control with the use of cameras connected to a processing unit, product line inspection can be conducted efficiently with minimal human efforts. At the same time, it also greatly prevents issues that arise due to human error. In the long-term, automated visual inspection helps to reduce the overall cost of production as less manpower is needed in the manufacturing quality control process. With machines responsible for inspections, humans can program and monitor the progress remotely. Manufacturing factories can also carry out inspection processes for a longer period of time resulting in better productivity. Lastly, the implementation of automated visual inspection is unchallenging as these systems are capable of adapting quickly to diverse products and surfaces.

Industrial Workplace Safety. Quality control for steels and metals are crucial as they play an important role in the majority of the engineering and constructions industry. It is important to ensure good quality of steel to prevent steel structure fatigue that leads to serious consequences. A defect in metal surfaces could result in weakness that leads to critical accidents. For instance, the presence of defects in steel surfaces can exhilarate great changes on a material's corrosion resistance and its mechanical properties. With surface defects, metals are prone to oxidation which weakens its structural integrity. This makes the metal unsuitable for further usage as it has lost its strengths and durability. Besides for metals used in electronic devices, surface defects tend to bring negative impacts on its electrical conductivity. These imperfections on metal surfaces bring hidden danger to the safety of users as well as affecting the performance of the end products. Hence, metals and steels must be inspected thoroughly to ensure good durability and strength in order to prevent any industrial accidents.

2 Literature Review

2.1 Deep Learning and Computer Vision

Implementation of Artificial Intelligence in manufacturing is getting more popular nowadays. For most AI-based defect detection solutions, deep learning and computer vision are used for visual inspection. A deep learning model is commonly empowered by artificial neural networks for the machine to learn through examples. The deep learning model will analyze input data and extract any common or underlying patterns beneath it for future prediction or classification. In automotive defect detection, a deep neural network is usually trained with many examples of defects it must detect. One of the most common deep learning algorithms is the Convolutional Neural Networks (CNN) where the model learns to perform tasks by computing algorithms and applying weights on the inputs. Each pixel value is analyzed where the neural network layers will convolve features extracted and recognize the landmarks for each type of defect. This information will then be interpreted and helps the deep learning model to learn, understand and recognize similar feature patterns in the future. Hence, the neural networks are capable of recognizing or distinguishing features from different classes in images by analyzing the typed edges and corners detected.

2.2 Image Segmentation

Image segmentation refers to the process of classifying image pixels to a certain class. This computer vision task could be referred to as a classification problem based on image pixels. There are TWO (2) types of segmentation techniques namely semantic segmentation and instance segmentation.

Semantic Segmentation
Semantic segmentation refers to the process of classification of each pixel to its corresponding or belonging label. This type of segmentation does not differentiate distinct instances of the same object label. Instead, it treats multiple objects from the same class as a single entity. For instance, if an image containing two dogs is passed into a semantic segmentation model, the returned output result of the segmentation will assign the same labels to both pixels covering the dog in the image.

Instance Segmentation
Instance segmentation refers to the process of classifying every instance of an object with a unique label. In simple words instance segmentation allows differentiation among similar object instances. For instance, the image with 2 dogs will now be assigned with different colours for pixels of each dog.

3 Methodology

3.1 Description of Dataset

The dataset used in this project is a surface defect database[1] constructed by Northeastern University (NEU) [6]. The image dataset consists of 6 types of defects namely crazing (Cr), inclusions (In), patches (Pa), pitted surface (PS), rolled-in scale (RS), and scratches (Sc). Each type of defect consists of 300 images which gives a total of 1800 gray-scaled images with resolution of 200 × 200 pixels. The dataset is divided into 1440 training

[1] Available at https://www.kaggle.com/datasets/kaustubhdikshit/neu-surface-defect-database.

images and 360 validation images. For each image, the defects are annotated to be used as ground truth for validation. In this study, we focus on patches and scratches which is the two most significant defect category in manufacturing process that is the largest contributing class that lead to the rejections [7] (Fig. 1).

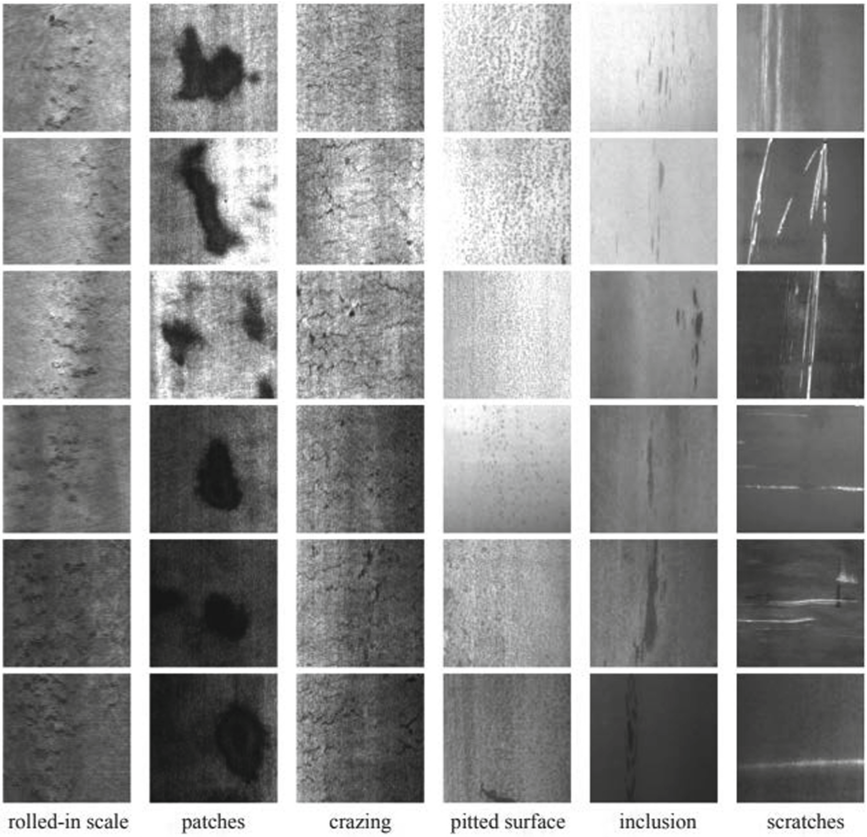


Fig. 1. Samples of six kinds of typical surface defects on NEU surface defect database. Each row shows one example image from each of 300 samples of a class

3.2 Technique in View

Figure 2 shows the image segmentation techniques that have been studied and implemented in this project. The techniques attempted are labeled with a green check mark.

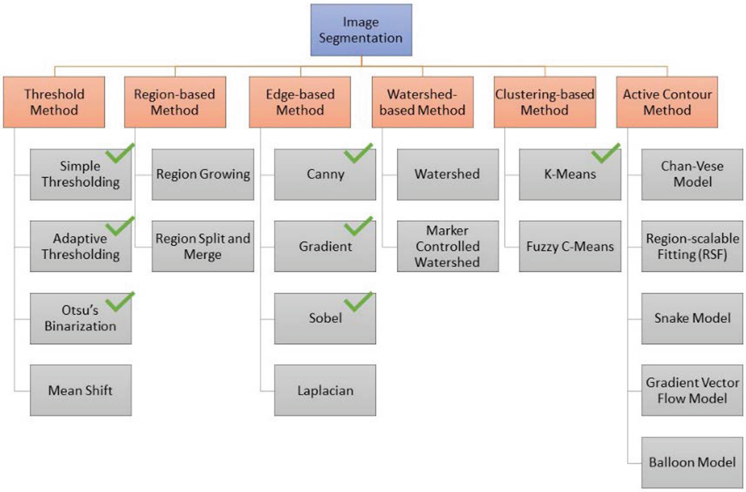


Fig. 2. Attempted Image Segmentation Techniques (Color figure online)

4 Result and Discussion

Based on the results obtained, we found out that patch defects could be accurately identified by using thresholding segmentation but not the edge-based segmentation. This could be due to the noise present in the patch defect images in our dataset. The metal surfaces with patch defects have uneven distribution of patches with different intensities. Therefore, it is difficult for an edge detector to clearly distinguish the patches from the background. Thresholding is a better way in this situation because the patches are darker so the patches and the background could be separated based on their pixel intensities. On the other hand, scratch defects are more distinctly detected using edge-based segmentation instead of threshold-based segmentation. This is probably because the scratches on metal surfaces in our dataset are mostly straight and uniform. The boundaries of scratches are easily identifiable. Therefore, an edge detector is preferable over thresholding.

The best thresholding technique for path defects is the Otsu's Binarization as it uses an optimal threshold that can be specified automatically and yet yields comparable results with a fine-tuned simple thresholded image. The simple thresholding technique is not selected as we want to avoid choosing a threshold manually every time, we take in an input image of different image brightness. Meanwhile, the Canny Edge Detector is shortlisted as the best technique to detect scratch defects. This is because it yields simply a black background with white contour representing the scratches that ease the localization process. The Sobel-filtered image and Laplacian-filtered image could not give a sharp representation of the scratch defects. Hence, when we perform localization, the scratch defects could not be located accurately (Table 1).

Next, we applied Bilateral filter on patch defects images and Gaussian filter on scratch defects image to denoise the images for better results of thresholding and edge detection since the techniques used are very sensitive to noises. The Bilateral filter is shortlisted

Table 1. Comparison of proposed method against ground truth for patch detects detection

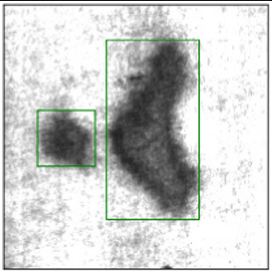
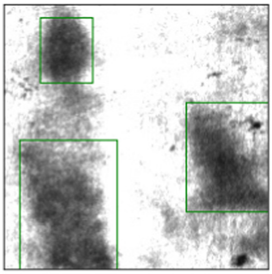
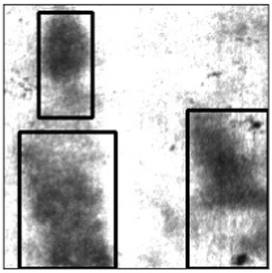
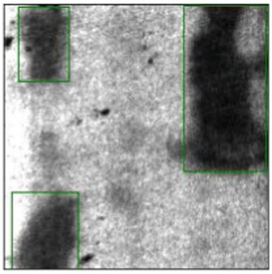
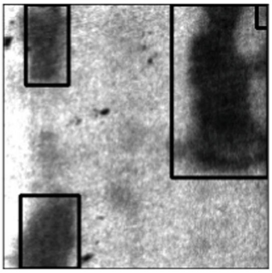
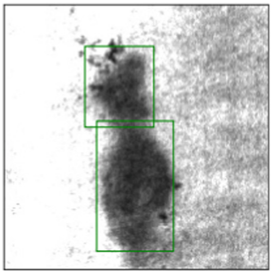
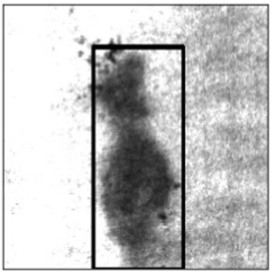
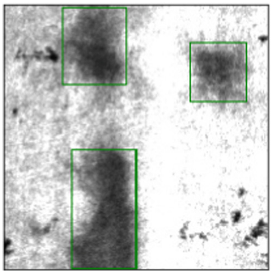
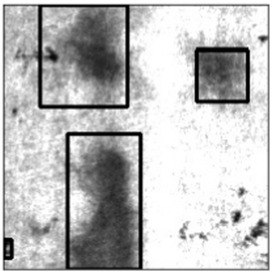
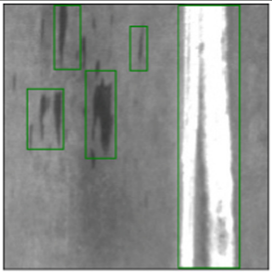
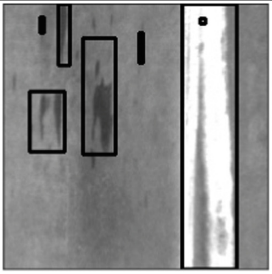
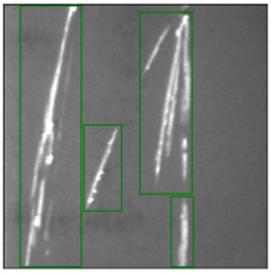
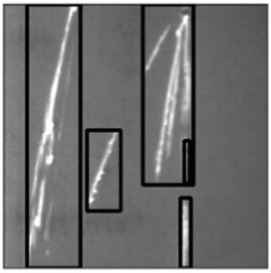
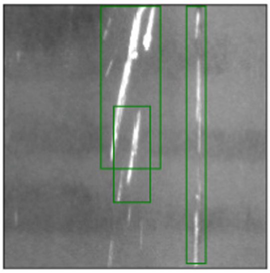
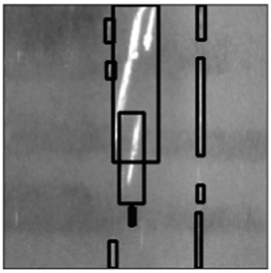
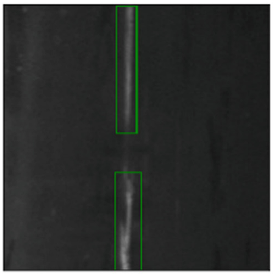
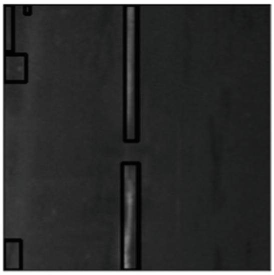
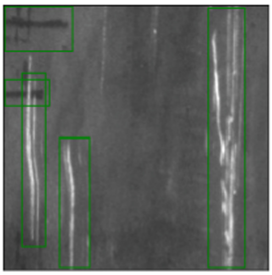
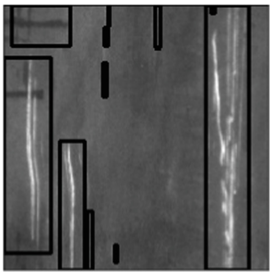
Ground Truth	Proposed Method
	
	
	
	
	

Table 2. Comparison of proposed method against ground truth for scratch detects detection

Ground Truth	Proposed Method
	
	
	
	
	

as it gives the best segmentation results with the least noise detection on patch defective metal. Meanwhile, the Gaussian, Average and Median filters return similar results of edge detection. Since Gaussian filters are the most generally used filtering methods in image pre-processing stages, it is selected to be applied on scratch defective metal. As a result, the contour of defects that we have obtained on each image helps us to successfully locate the defects with bounding boxes.

Moreover, the opening operation performed on patch defects images allows us to retain the huge chunks of patches and remove small objects in the foreground. By doing so, we are able to obtain a clearer highlighted defect area for better localization results. In contrast, the closing operation is used on scratch defects because we want to connect the lines or strikes as a result of edge detection on the surface of scratch defects images. This operation helps to improve the localization results on scratch defects images.

Finally, we observed that some IoU values computed for the patch and scratch defects localization have extreme differences. For example, there are 2 detections with 0 IoU values in the patch defects detection, as well as the scratch defects' detection. The reason for this phenomenon is that we extract only the largest bounding box from the ground truth and the detection to compute the IoU. However, the largest bounding box in the ground truth does not necessarily match the one detected by our algorithm.

Nevertheless, we have obtained satisfactory results as most of the defective images tested have an IoU value above 0.6 as illustrated in Fig. 3 and Fig. 4. Besides, all tested images are returned with clear bounding boxes surrounding the defective regions. By visual inspection, the localization of defects is considered accurate as it is impossible to acquire bounding boxes which are identical with the ground truth (Table 2).

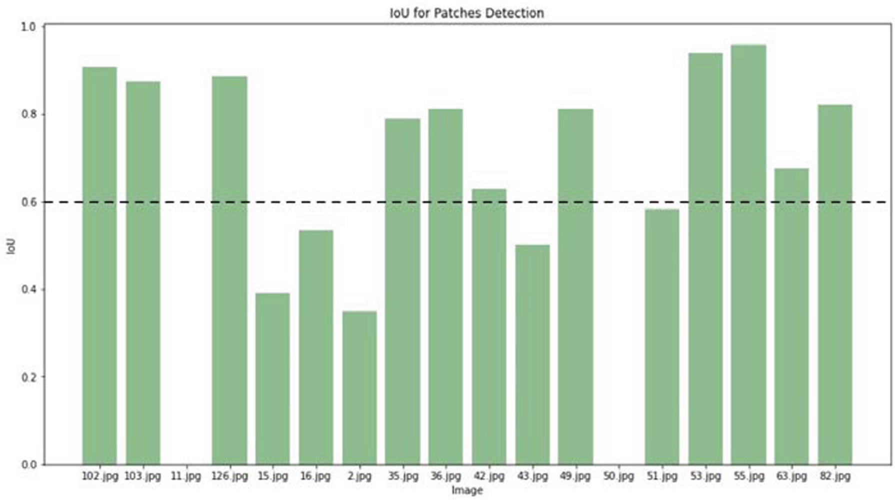


Fig. 3. Evaluation of patch defects detection using IoU

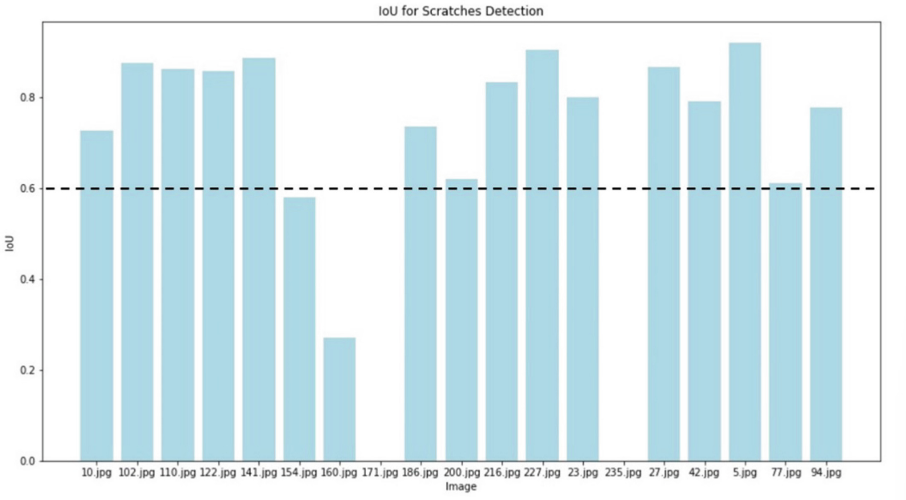


Fig. 4. Evaluation of scratch defects detection using IoU

5 Conclusion

This study has achieved all the objectives mentioned in the previous section.

Foremost, the most suitable image segmentation method for patch and scratch defect respectively are successfully identified. In this project, a total of three image segmentation methods are attempted namely threshold-based segmentation, edge-based segmentation and clustering techniques are implemented and compared for detecting patch and scratch defects. We successfully identified that the threshold-based segmentation method is more suitable for patch defects whereas the edge-based segmentation method is more suitable for scratch defects. Among the attempted threshold-based segmentation, namely simple thresholding, adaptive thresholding and Otsu's Binarization, we discovered that the best technique to detect patch defects is Otsu's Binarization. A clear contour is observed when tested with patch defects images. On the other hand, Canny edge detection algorithm performs the best with scratch defective images as compared to other edge-based segmentation methods implemented such as Sobel and Laplacian. There is a clear distinction in the output edge lines between defect areas and non-defect areas.

Furthermore, the objective to accurately localize patch defects on at least 10 metal surfaces is achieved. In our project, Otsu's Binarization is the final shortlisted technique for patch defect detection and is further optimized in order to achieve better results. We performed several optimization techniques such as image blurring and morphological operations to improve the output mask. After we have successfully distinguished the defective region from the non-defective region, we localize the defect regions by drawing bounding boxes and displaying them on the original image. As a result, we can see clear highlights and accurate visualization of patch defects in more than 10 tested images.

Moreover, the objective to accurately localize scratch defects on at least 10 metal surfaces is achieved. In our project, Canny edge detection is the final shortlisted technique for scratch defect detection and is further optimized in order to achieve better results. We performed several optimization techniques including defining a function to auto-determine the optimum threshold, image blurring and morphological operations to improve the output mask. After we have successfully distinguished the defective region from the non-defective region, we localize the defect regions by drawing bounding boxes and displaying them on the original image. As a result, we can see clear highlights and accurate visualization of scratch defects in more than 10 tested images.

Lastly, the proposed system is capable of achieving an Intersection over Union (IoU) value for at least 0.6 for both defect types. After testing the selected 18 images with the shortlisted and optimized segmentation method, the results are compared and evaluated against the ground truth provided in the original dataset through computing the IoU value. As a result, the system successfully detects defects with more than 0.6 IoU value in more than 10 images tested for each defect type.

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