CHAPTER 1
INTRODUCTION

1.1 Background

In the world of construction and engineering, steel is the most important material. Therefore, steel must be in good condition and suitable for use. Recently, there are still many steel companies that checking quality of steel manually or see it through with their bare eyes, but it is obviously dangerous for human workers. Because manufacturing uses high temperatures of 700° to 900° Celsius [9]. Checking steel manually is not very effective and efficient because it is hard to see small defects on the surface of the steel when the temperature is high [9]. The manual method of detecting surface defects in steel has poor performance in real time and has a high rate of false inspection accuracy. So that, this method is not only high risk and not ideal in determining the quality of steel.

Under ideal working conditions, the accuracy of the inspection of surface defects in steel is only about 70% maximum for trained and experienced workers [10]. Hence, the researchers now applied the advanced of deep learning technology to various fields including the inspection of defects in these steel surfaces. In the steel defect inspection system, the mechanism of this steel defect inspection system generates an image by scanning the steel surface, and the processor performs the surface defect inspection [10]. It means, this system can increase the accuracy of the inspection of steel surface defects and avoid very high risks in human work.

This advanced inspection technique focus on steel's algorithm to check the defect on that steel surface. In the proposed model of examining steel surface defects, deformable convolutions enhancing the backbone network first extract complex features from multi-shape steel surface defects. Then the feature fusion network with pyramid balanced features generates high quality multi-resolution feature maps for multi-size defect inspection. Finally, the detector network achieves the localization and classification of steel surface defects [11]. Thus inspection technique can emphasize that there are defects on the surface of the steel.

Moreover, the types of steel surface defects not only concentrate on the classification of various images to get a full understanding of them, but also try to precisely estimate the concept and position of objects found in each drawing. Object inspection, as one of the most basic computer vision problems, can provide useful information for semantic understanding of images and videos, and is connected to a number of applications, including image classification. The classification task can only find defects in images with the highest confidence category, not the number of causes of defects. To detect steel surface defects through images, it is not only necessary to place the image but also to measure the size of the image resolution and also the image scale. In the dataset from Northeastern University (NEU), for all images have the same resolution 200×200 pixels, but the size of each defect is different. A scale converter is needed so that the accuracy of each defect inspection can be increased. Therefore, one feature is added, namely multi-scale so that the image can enlarge and reduce the scale by itself to make the defects appear more obvious [12].

Many architectural methods are used to inspect defects on steel surfaces that only use ordinary Convolutional Neural Networks but do not get good accuracy. There is also a single-stage method that has fast inspection but not so high accuracy because the system detects steel surface algorithms using only features basic map of deep learning without a proposal box to process data into more detail. Therefore, the author uses a multi-stage deep learning system so that there is a proposal box assistance that will increase accuracy so that it is hoped that this thesis will detect the types of defects on the steel surface by classifying each type of defect and also localizing every defect on the steel surface and getting the desired accuracy [13].

Based on those risk about the vulnerability of human workers in the manual inspection of steel, safer steel inspection is highly recommended. So that, one way to safely inspect steel defects for human workers is to use Digital Image Processing Based on Multi-Stage Deep Learning. This method primarily employs an image level classifier that is entered into a proposal box and then repeated. It outperforms conventional learning approaches by utilizing specially designed image features and CNN in standard mode.

This method is one of the best solutions to overcome these risks. Therefore this research about Digital Image Processing Based on Multi-Stage Deep Learning is feasible to conduct. Because human workers do not need to inspect the defects on the steel surface directly by their own eyes, and of course this ensures the safety of human workers. Research on that defects inspection on steel surface using digital images has also been carried out.

A previous study entitled ”A Steel Surface Defect Inspection Approach Towards Smart Industrial Monitoring” conducted research on the detection of defects on steel surfaces. This study uses the NEU-DET dataset and develops from the baseline model, namely Faster R-CNN, into a model which is Multi Stage deep learning. However, previous research explained in examining defect inspection with the single-stage deep learning. That method used a sample of 1786 images from the North Eastern University (NEU) data set with 6 different classes of disabilities. The types of defects are Crazing (Cr), Inclusion (In), Patches (Pa), Pitted Surface (PS), Rolled-in-scale (Rs), and Scratches (Sc). Previous research obtained an mean Average Precision (mAP) of 80.6% and for each class Avaerage Precision (AP) of 85.9% for inclusion defects, 92.9% for Patches, 90.3% for Pitted Surfaces, and 88.1% Scrathces. The AP value is already high for detecting a defect, while for Crazing defects it is 61.5% and 64.8% for Rolled-in-scale.

On previouse research [14] also identification of steel surface defects by multi-stage method with Faster RCNN by changing replacing parts from conventional a convoluted network with a deformable convoluted network. In this study, the obtained mAP is 75.2%. Therefore, in this thesis is examine six classes of steel surface defects from the NEU dataset to increase the mAP and AP of Crazing and Rolled-in-scale defects to above previous of steel surfaces using the Multi-Stage Deep learning method using architecture Faster RCNN, Cascade RCNN and DetectoRS.

1.2 Problem Formulation

The problem in this thesis are how to create architecture multi-stage deep learning that can inspect defect of steel surface. How to get the mean Average Precision (mAP) above to 80.6% and Average Precision (AP) of Rolled in Scale above 64.8%.

1.3 Objectives

The purpose of this undergraduate thesis is to classify and localize 6 classes of steel surface defects, and still achieve the AP that has been achieved by previous research for the Crazing, Inclusion, Patches, Pitted Surface, Scratches defects classes, also increase the mAP and AP for the Rolled-in-scale class to above previous results using Multi-stage deep learning.

1.4 Scope of Research

1. Computer or Laptop
2. Google Colab Pro
3. Browser and Internet connection is needed

4. Collection of six classes of defect of steel surface datasets from Northeastern University (NEU) are Crazing (Cr), Inclusion (In), Pitted Surface (PS), Rolled-in-scale (Rs), and Scratches (Sc)

5. Image format is .jpg

6. Image resolution are 200×200

7. Performance parameters measured from the system are Recall, Average Precision (AP), mean Average Precision (mAP), and Frame per Second (Fps)

1.5 Research Methods

1. Literature Study from several paper and journal

2. Collecting datasets

3. Developing deep leaning algorithms

4. Realization

5. Analyzing