Convolutional Neural Network-Based Metal Surface Defect Detection

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***Abstract*—The visual inspection using computer vision technology is growing rapidly nowadays. The number of industries that relies on automatic defect detection is rising due to some limitations when doing defect detection manually by a worker. The automatic defect detection also benefits the industry because it will help increase the quality control of production line and in the end it helps to maintain the product quality. A convolutional neural network is developed in order to classify six types of defect on metal surface. The result is promising, the developed model able to recognize 95.8% of testing data correctly.**

***Index Terms*—metal surface defect detection, convolutional neural network, automatic defect detection**

I. Introduction

Nowadays, many company is competing to increase their product quality in order to get more customer to buy their product. Other than that, defect inspection using computer vision technology is an important task in various industries [1]. In the past, defect inspection is done manually by worker. Unfortunately, manual defect inspection by worker is very subjective and time-consuming. In order to solve this issue, many researcher proposes idea to do automatic defect inspection by using help of computer vision technology.

Prior to this day, there are a lot of research conducted to detect the defect on various materials, such as flat steel surface [2], tunnel inspection [3], concrete crack [4], fabrics[5], and textile [6]. Each materials requires a specific method and algorithm to detect the defect on the materials. The method and algorithm also depends on the client needs, such as processing time, hardware specification, and budget.

Generally the method of defect detection can be divided into two categories, defect classification and defect localization [2]. The defect classification categories has main goal to classify the image pixel as a defect or non-defect pixel. This categories not only classify defect or non-defect, it also classify the kind of defect that occur in the image. Usually there are several types of defect that happen on metallic surface, these are inclusion, crazing, patches, pitted, rolled, and scratches.

The defect localization categories has main objective to classify the defect types and predict the location of defect on the image. This category requires more advanced algorithm and better hardware specification due to the increase of computation complexity in order to reach the objective. In this category, firstly, the algorithm will classify the types of defect that occur on the image pixel, it will classify the image pixel into one of types of defect or non-defect. If defect is detected, the algorithm will try to predict the dimension of the defect in order to get the pixel coordinate point that will be used to make a bounding box for the defect.

In this paper, author will conduct research on classifying defects on metal surface using NEU surface defect database [7]. The image from database will be classified into 6 types of surface defects, rolled-in scale, patches, crazing, pitted surface, inclusion, and scratches. The author will use convolutional neural network algorithm to classify the images into its types of defect that occur on the metallic surface.

II. System Architecture

A. Convolutional Neural Network

The convolutional neural network is a type of neural network that uses a convolutional function in one or more of its layer. The architecture of the convolutional neural network consists of two parts, the feature extractor subsystem and the classifier subsystem. Feature extractor subsystem is the most important part which differs convolutional neural network with another feature extractor method [8].

The feature extractor subsystem consists of convolutional layer and pooling layer. The convolutional layer is the main part which is used to extract the full information of the tensor input data, while the pooling layer is used to reduce the spatial size of the data. The output from the feature extractor subsystem is used as an input to the second part of the convolutional neural network, i.e., the classifier subsystem [8].

B. Datasets

The author will use datasets from NEU surface defect database [7]. This database contains of 1800 images of surface defect on metal materials. All 1800 images is in grayscale images and has resolution of 200x200 pixels. The database is contain of six different kinds of typical surface defects, these are rolled-in scale, patches, crazing, pitted surface, inclusion, and scratches. The six types of surface defect each will has 300 sample images.

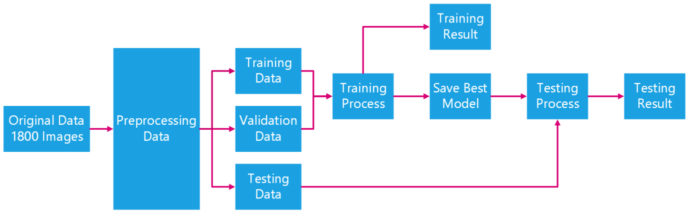

Fig. 1. Flow diagram of training and testing procedure

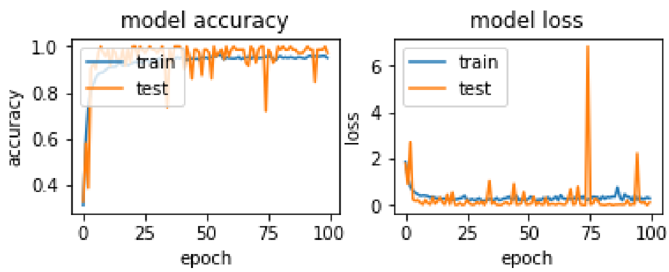

Fig. 2. Model accuracy and model losses on training process

III. Experiment

In this experiment, the author is split the data into three parts, namely train data, validation data, and test data. The train data is consist of 1656 images that will be used as train image for the system to learn the pattern. Meanwhile the validation data is consist of 72 number of images is used to validate the learning result of the algorithm for every 10 training epochs. Then, the test images is used to test the best model that resulted from the training procedure. The test images is consists of 72 images and those images is never seen by the model in the training procedure. The flow diagram of training and testing procedure is shown on Fig. 1.

This experiment will use a convolutional neural network that consists of feature extractor subsystem and classifier subsystem. The feature extractor subsystem utilize three layer of convolution layer and pooling layer. Each of the convolution layer and pooling layer use kernel with size of 2x2, strides of 1 and no padding. The convolution layer also utilize an activation function which in this experiment, the author is using ReLU activation function.

For the classification subsystem, the 2D matrix from feature extractor system is being flattened first in a flattened layer. After that, the data is send to the dense layer which employs an activation function and consists of 256 nodes. A layer of dropout layer is also utilized in this subsystem to decrease the chance of getting an overfitting result. Finally, the last layer in this subsystem is output layer which consists of six nodes that represents the number of defect types on the datasets. The output layer also use an activation function called Softmax activation function.

The training procedure in this experiment is done using help of Tensorflow library to create the convolutional neural network model. On the training process, the author utilize Cross Entropy as the loss function and RMSprop algorithm as the optimizer to make the training process faster and yield a better performance. In addition, the author also train the network for 100 epoch with data batch size of 32. The training time takes around 50 minutes to finish the 100 epoch training process. During the training procedure, it will produce the accuracy value and loss value. The Fig. 2 represents the accuracy and loss during the training procedure.

After the training procedure is finished, we use the best model that yield highest accuracy and lowest loss for the testing procedure. The test data will be fed into the best model and the model will classify each image on the test data into its type of defects. The result of the testing procedure is our model can classify up to 95.8% accuracy. The model able to classify 69 out of 72 images correctly and only have three incorrect classification. This proves that the convolutional neural network that being developed is working properly to classify the defect in metal surface.

IV. Conclusion

The convolutional neural network has been developed to classify the image into six type of defect on metal surface. The result is promising as the developed model can reach up to 95.8% accuracy and only have three incorrect images classification out of 72 images on testing data.

Acknowledgment

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks . . .”. Instead, try “R. B. G. thanks…”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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