END SEMESTER

REPORT ON

DETECTION OF DEFECTS IN FLAT SHEET STEEL USING AI

BY

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ABSTRACT

Classification of steel surface defects in the steelmaking industry is essential for the analysis of causes that make defects. The defect rate of product and mass defect in stell are drastically reduced through this process. Recently, Deep Learning has been used for defect detection using Convolutional Neural Networks (CNN). The defect classification using CNN achieved high performance compared to the existing rule-based method.
However, learning CNN requires hundreds or thousands of images.

The implementation of automatic visual recognition of steel surface defects provides critical functionality for quality control of steel sheet production. In this report, we present a compact yet effective convolutional neural network (CNN) model, which emphasizes the training of industry samples of steel surface profile and incorporates U-Net architecture to achieve fast and accurate steel surface defect classification.

INTRODUCTION

The automation and intellectualisation of the manufacturing processes in the iron and steel industry need the strong support of inspection technologies, which play an important role in the field of quality control. Undoubtedly, steel sheet is one of the most widely used materials in modern industry. However, steel sheet may be subjected to defects by materials, equipment, etc. during the production process, resulting in various defects on its surface, e.g., scratches, surface crazing and rolled-in scale, which can cause substantial economic losses to the enterprise. These visually observable defects will cause changes in steel material properties such as corrosion resistance, wear resistance, and fatigue strength, and significantly decreases the quality of the final product. They are leading to huge economic loss to the enterprise.

The principal objective of steel surface inspection is to accurately predict defect categories, providing important information for identifying and subsequently suggesting to correct causative factor. Traditionally, the surface quality of steel strips is manually inspected by human experts. However, the manual inspection process is highly subjective, labour-intensive and too slow to facilitate real-time inspection tasks. Therefore, the necessity of real-time accurate inspection of surface defects is very high in the iron and steel enterprises. Steel sheets were among the essential construction materials; the significance of this study from civil engineering point is also considerable. The traditional defect detection process of the steel consists of four sub-processes:

1. Image acquisition
2. Rapid detection
3. Feature extraction
4. Defect classification

Image acquisition is to make the defects visible. Acquiring defect images and locating the positions of the defects is done in rapid detection. Then the feature extraction, as one of the crucial tasks of a surface inspection system, is mainly to describe the defect characteristics. The last component is called defect classification. In this sub-process, the extracted features are attached to class labels employing a classifier.

In recent years, deep learning technology in the field of pattern recognition emerged and has already been widely used. Deep learning technology greatly improves the accuracy of image classification. Convolutional neural networks have shown great results in image segmentation and classification. However, due to the constraint of high-quality image requirement with proper labels for the training model, these deep learning techniques have not been widely used in the steel strip surface defect recognition. It is due to this reason that we decided to use CNNs for this task. We are trying to show that it is an effective method and can also minimise costs during the whole process.

DATASET

The dataset we are using for this task has been downloaded from *Kaggle.com*. The dataset was uploaded as part of a Kaggle Competition by *Severstal*, a company that manufactures steel. This is mostly industrial data. The task given was to identify which part of the steel contains the defect and also to determine the type of defect. The dataset has 12,568 images of steel sheets and there are 4 different types of defects.

The 4 different types of defects and a sample image are shown below.

1. Roll mark

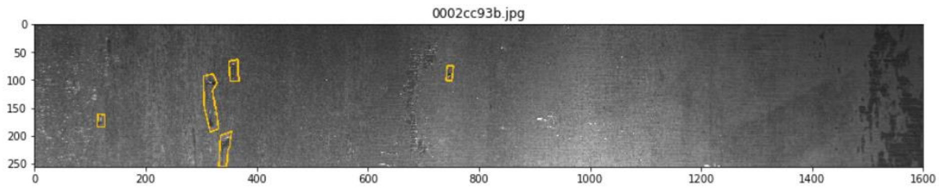

Figure 12. Roll mark defect

2. Longitudinal scratches

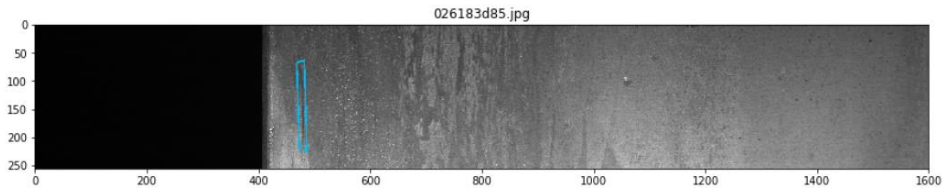

Figure 13. Longitudinal scratch defect

3. Pockmark

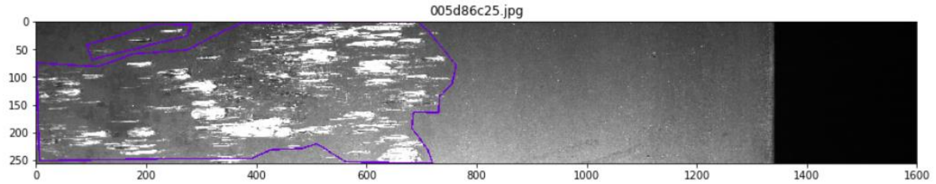

Figure 14. Pockmark defect

4. Scale

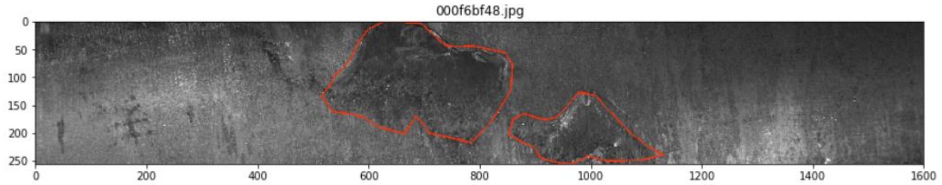

Figure 15. Scale defect

The images have been uploaded as a zip file and the segregation and classification of the defects have been uploaded in a csv format. The segregated defect area has been stored in a run-length encoded format.

Upon conducting an exploratory analysis of the given dataset, we found that the dataset was skewed. The number of defects of class 3 is way more than the number of other defects. This has been represented in the graph shown below. This requires the model to be robust enough to capture the characteristics of the other classes with comparatively fewer examples.

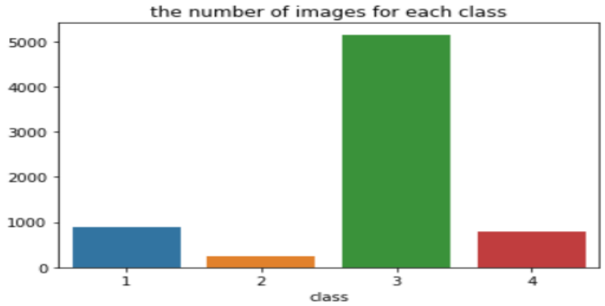

Figure 16. Number of samples for each defect

METHODOLOGY

We are using Convolutional Neural Network (CNN) architecture for identification and classification of surface defects. Convolutional Neural Network (CNN) is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNN is considered as a unique instance of artificial neural networks (ANNs), which are inspired by the human visual cortex.

Unlike traditional fully connected ANNs, neurons or units in CNNs are designed for a squared feature map and connection between each neuron of the feature map in each layer to a small set of neurons in the previous layer is sparse. In the CNN architecture, the 'sharing' of weights over processing units reduces the number of free variables, increasing the generalisation performance of the network. The higher-level features are class-sensitive, whereas lower-level features are generic. Therefore, the high-level feature representations are more useful and critical for classification, where CNN prove more useful in forming the hierarchical feature representations from low level to high level. These discriminative feature representations improve classification performance significantly. CNNs are an end-to-end auto-learning model with a minimal need for human design. It enables us to develop trainable architecture which combines the feature extractor and classifier by operating on raw pixels of the two-dimensional image directly.

We need three basic components to define a basic convolutional network.

1. **The convolutional layer**
2. **The Pooling layer**
3. **The output/classification layer**

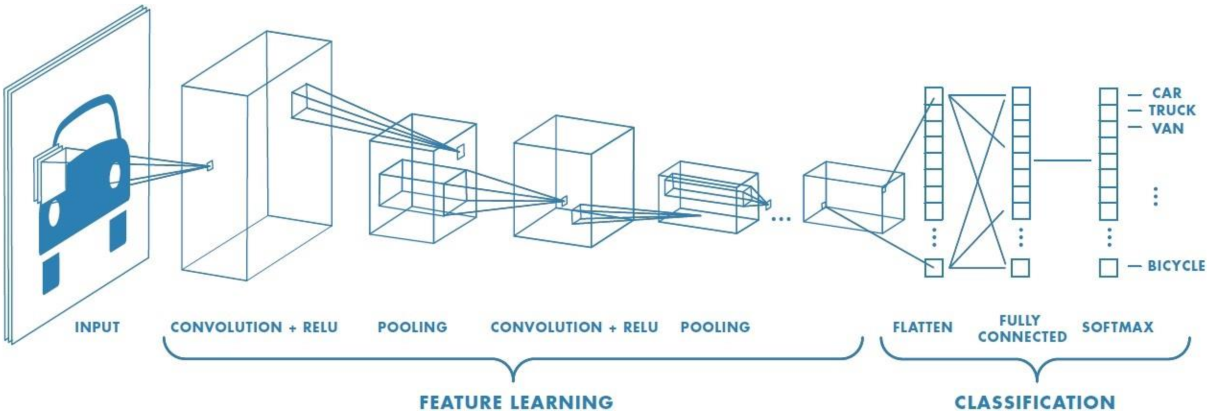

Figure 17. Sample of a CNN architecture

Convolution Layer

Convolution is the first layer to extract features from an input image. It is a mathematical operation that takes two inputs, such as an image matrix and a filter or kernel. The element involved in carrying out the convolution operation in the first part of a Convolutional Layer is called the **Kernel/Filter.** The objective of the Convolution Operation is to extract the high-level features such as edges, from the input image.

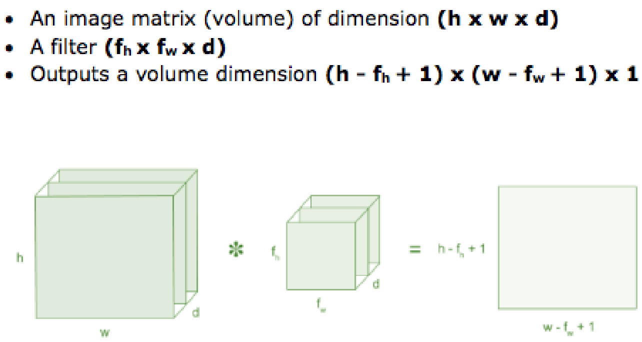

Figure 18. Representation of a convolutional layer

Pooling layer

Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature. The computational power required is reduced by this so as to process the data through dimensionality reduction. Furthermore, it is useful for extracting dominant features which are rotational and positional invariant, thus maintaining the process of effective training of the model.

Classification — Fully Connected Layer (FC Layer)

A Fully-Connected layer is a (usually) cheap way of learning non-linear combinations of the high-level features as represented by the output of the convolutional layer. The flattened output is fed to a feed-forward neural network and backpropagation applied to every iteration of training. Over a series of epochs, the model is able to distinguish between dominating and certain low-level features in images and classify them.

There are various architectures of CNNs available for specific purposes. We are using **U-Net** architecture which is considered to be a fully connected CNN. The typical use of convolutional networks is on classification tasks, where the output to an image is a single class label. However, in many visual tasks, especially in biomedical image processing, the desired output should include localisation, i.e., a class label is supposed to be assigned to each pixel. In defect detection localisation is necessary. Also, this network is capable of handling larger volume of training data.

Loss Function – Cross-Entropy Loss

The most commonly used loss function for the task of image segmentation is a pixel-wise cross-entropy loss. This loss examines each pixel individually and compares the model prediction with the target vector, and then later, averages it over all pixels. It is given by the following formula.

$$-\sum_{classes} y_{true} \log\left(y_{pred}\right)$$

The smaller the Cross-Entropy loss, the better the model.

Architecture model

The network architecture is illustrated in the figure below. It consists of a downsampling-contracting path (left side) and an upscaling-expansive path (right side). The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. At each downsampling step, we double the number of feature channels. Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution

(“up-convolution”) that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer, a 1x1 convolution is used to map each 64- component feature vector to the desired number of classes. In total, the network has 23 convolutional layers.

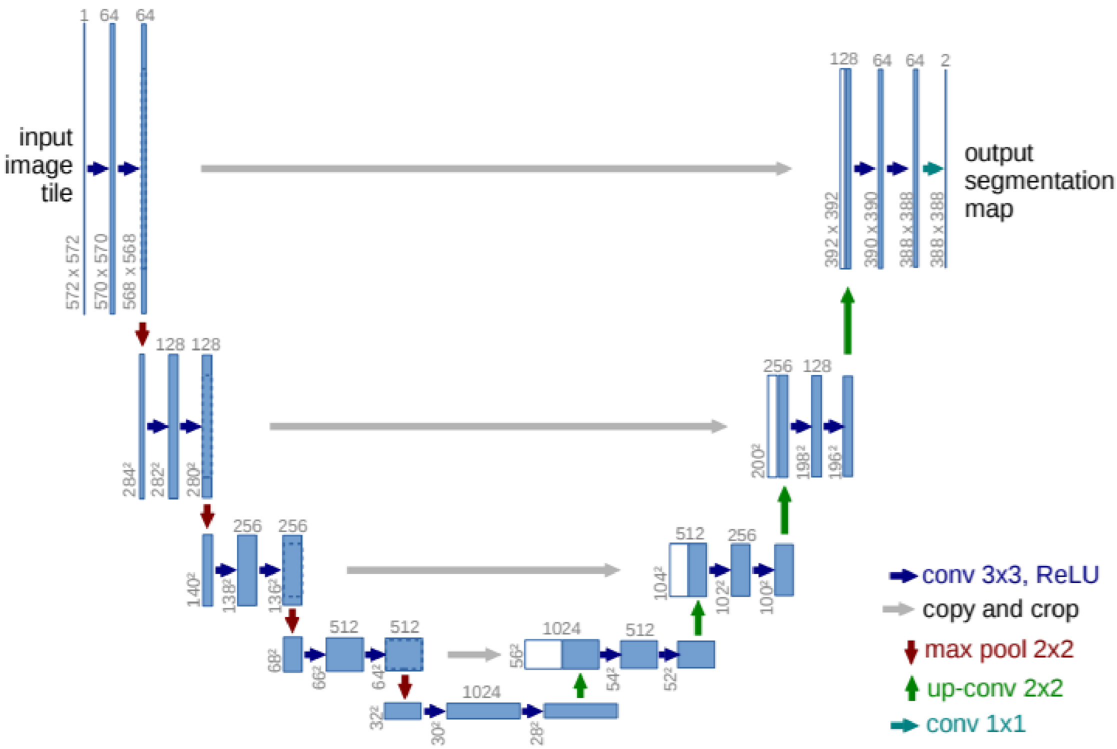

Figure 19. U-NET CNN Model Architecture

RESULTS

The value of the loss function after each epoch for both the training and validation set has been recorded below.

EPOCH NUMBER	TRAINING LOSS	VALIDATION LOSS
1	1.0195	0.9951
2	0.9293	0.8884
3	0.7924	0.7821
4	0.7061	0.7592
5	0.6619	0.6620
6	0.6397	0.6473
7	0.6197	0.6452

A graphical representation has also been attached below

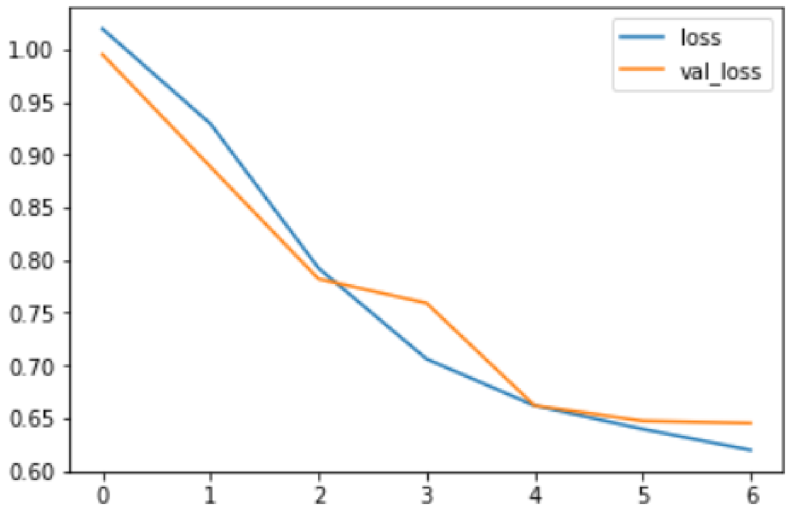

Figure 20. Results

We observe from the results obtained that both training and validation loss steadily decreases and the number of epochs increases. Due to computational constraints, we were unable to perform more than 7 epochs as each epoch was taking approximately 2 hours to finish. However, the fact that the loss still hasn’t converged means that there is more potential for the model to improve, as long as there is better equipped to conduct the experiment.

A sample image has been taken from the test set to check how our model has performed. The image before passing through the model and after passing through the model has been attached below.

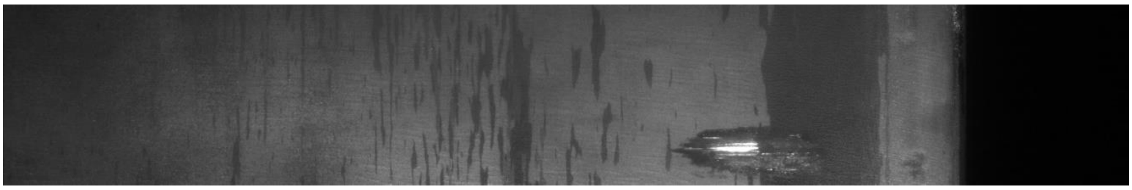

Figure 21. Image before passing through the model

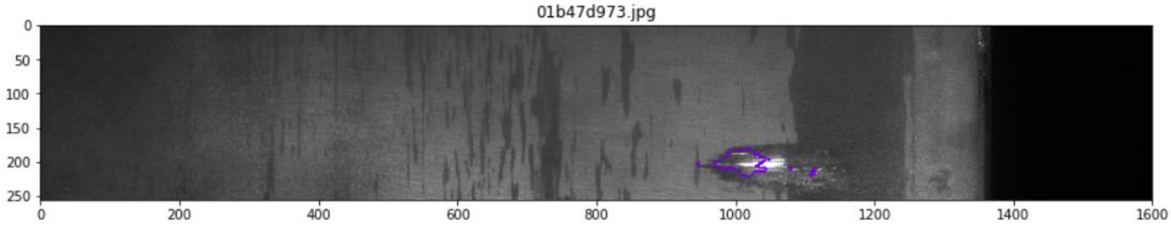

Figure 22. Image after passing through the model

Here we see that the model has approximately located the defect and classified it as defect number 3, indicated by the purple coloured border. However, it hasn’t identified the area of the defect perfectly.

CONCLUSIONS

Even though the model is not industry ready, with better training data and more efficient and powerful computers, CNNs can indeed be used to successfully classify defects in the sheet steel industry. This can save a lot of money and time in the manufacturing process and can hence, improve the steel production industry overall.

RELATED WORKS (LITERATURE REVIEW)

The most generic method of defect detection of steel surfaces is rule-based. However, CNN architecture requires hundreds or thousands of images. Quality Although many of those traditional methods have achieved moderate results by means of some advanced features and classifiers, they have three main drawbacks:

1) The dependency of powerful expert knowledge for manually designed features and complicated design method

2) The design of features is done independent from the design of the classifier, so the designed features might not be the best for the classifier.

3) Different tasks had different design of features and classifier.

In order to overcome the above shortcomings, our work uses the CNNs to classify the surface defects of steel sheet, which can directly learn some better representative features from the labelled images of surface defects by supervised learning.

There are numerous works in this topic using different classifier models and optimisation methods acknowledging the drawbacks of the current deep learning methods. Most of the works recognized the feasibility of CNNs for feature extractor and classification. One recognized work of *S Zhou et al*, published in 2017, proposed a classification based on the convolutional neural network, which performed very good. Though accuracy was high it needed lots of training data sets and the author didn’t analyze the effects of noise and the size of training data sets.

There were several other works without using CNNs.In the paper published in 2012, *B. Suvdaa1, J. Ahn2 and J. KoWe* used SIFT for defects regions detection and features extraction for the following SVM classification. This approach was able to generate many feature points for training the classifier from a few images.They proposed a voting strategy for the final decision that handles the problem of multiple outputs of a given input image with a specific defect type. Though the model did not require huge magnitude of datasets, the results were not that accurate enough compared to CNN models.

Based on the research in recent years, we can find that implementation Convolution neural network with adequate dataset labelling, classification problems can be dealt with higher efficiency. Training the model (image feature extraction) with a large amount of data in a specific field and then applying this model to the identification of steel sheet surface defects, can well solve the shortcomings of the number of industrial steel strip surface images.

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