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Classification and Segmentation Model for Steel Defect Detection

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Abstract

Machine learning achieved impressive recognition rate in image classification task. In order to exploit those capabilities of machine learning algorithms, this paper represents classification and segmentation of surface defects. Nowadays, Automatic defect recognition is one of the research key areas in steel production. The authors of this article have understood the inadequacies of the previously available detection procedure in noticing slight and complex defect marks and would like to share a new enhanced target finding algorithm in steel shallow defect detection. For classification author has used pre-trained InceptionResNetV2() model by keras. In training the model, the author builds four segmentation models to train four defect classes separately. The results show excellent defect detection with accuracy of 94 percent in comparison of Support Vector Machine model which gave us accuracy of 84 percent only.

1. Introduction

Metals consisting of surface defects are eliminated and rejected at the time of manufacturing to avoid any further error. Pre-detection techniques reduce cost of manufacturing and further damage to the products. One of the most important and required operation on image is to recognize and categorize the various kinds of defects. The final product can be rejected or accepted by the customer based on the correctness of required features. The products are automatically sorted and packed but the final checking is done by hand to assure the correct dimensions and features. Examination by humans is very time consuming, costly and are not error free. These human judgements depend on previous knowledge and experience. It is very important to check the quality of the product before it gets delivered to the customer. Continuous inspection is required for quality enhancement [1]. Plates of steel are crucial resources for the vehicle manufacturing, national security industry, equipment manufacturing, biochemical manufacturing, light industry, etc. Though, because of the difficulties of raw resources and technology, numerous kinds of imperfections will be formed in the making procedure of steel plates—especially blows, coatings, curling boundaries, holes, scratches, and other imperfections on the surface. Automatic recognition of steel exterior imperfections is very significant for product superiority control in the steel manufacturing. Though, the old-style methods cannot be well useful in the manufacture line, as of its low accurateness and slow execution speed.

In this work, we propose a classification model for defect detection, which can meaningly improve the accurateness and decrease the average execution time of the procedure. The organizational assembly of this research paper is as follows: Section 2 presents the work done on this problem in past. Section 3 comprises the proposed work in detail. Sections 4 shows the experiment setup to prove the accuracy and competence of the algorithm, and compare our outcomes with other approaches. Finally, Section 5 précises the work and draws a conclusion.

2. Literature Review

In the previous periods, investigators have established a variety of procedures [2] to detect defects on steel exteriors. One of the old-style methods is built on statistical evidences and image features. This technique needs investigators to manually plan some image features and conduct statistical study on these features to obtain the detection outcomes. The usually used approaches are Sobel [3], canny [4], hog [5], local binary patterns (LBP) [6], Fourier transform [7], wavelet transform [8], etc.

T. Arthi, M, Karthi and M. Abinesh's [9] worked on Discovery and study of surface defects on alloys using Wavelet transformation. Their practice was calculation of variance, standard deviation, mean, skewness and kurtosis from the developed image. Mayuri Dharma Shinde's [10] work on detection and identification of defects on Industrial pipe. The methodology they used was Morphological logics, Dilation and Erosion Operations. Y. Ramadevi, T. Sridevi, B. Poornima, B. Kalyani's [11] work on Segmentation and Entity Recognition using Edge Detection Methods. Their methodology was based on EM Algorithm and Genetic Algorithm. Gagen Kishore Nand [12] used a methodology of entropy

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segmentation for defect detection of steel surfaces.

Image segmentation can be done by numerous edge detection methods like Prewitt, Roberts, LoG, Genetic Algorithm and EM algorithm. Various methodologies like Morphological image processing and statistical classification method, Entropy segmentation, Contrast adjusted Otsu's technique (for imperfection detection in titanium coated aluminum surfaces) have also been used. Each method has its own merits and demerits. It is clearly understood that some methods are speedy but give less accuracy. Whereas, some methods have high accuracy but have complex calculation speed. From time to time, these methods have evolved into a better form to give better accuracy. In general, there is no perfectly proposed methodology to detect defects but the ones with highly accurate results are used.

3. Methodology

This section provides us with our problem statements along with data set and solution approach.

3.1. Problem Statement

Given an image, authors task is to classify the defect and locate the segmentation of the defect. For each image author must segment the defects if it belongs to each of the class.

3.2. Solution Approach

As this problem deals with binary classification, multi-label classification and segmentation, there can be many approaches to solve this problem, the pipeline strategy used is shown in figure1., where firstly author has filtered the defected images and then passed it through multi-label classification where single image can belong to more than one class. We directly take the results and pass it to the four segmentation models separately belonging to (ClassId= [1,2,3,4]).

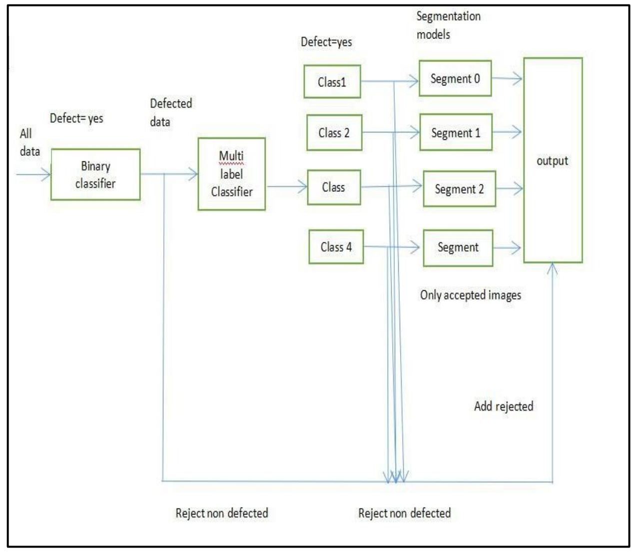

Figure 1. Pipeline Strategy

4. Experiments and Results

4.1. Exploratory Data Analysis

Author used EDA to get to know more about data. Author firstly saw the distribution of defected and non-defected classes. Figure 2. shows that the problem is a well-balanced binary classification problem, after this author finds out the class count distribution as shown in Figure 3., which shows a challenging problem as our multi-label classification is imbalance in data, as class-2 defected images are very less in data while class-3 defects are very high in number, class -3 and class-4 are somewhat balanced.

4.2. Binary Classification

Author Splits the data into train-CV randomly. Author by reading finds that the train and test data are not same so it is advisable to augment the data to solve the problem to a little extent. Then firstly for the binary classification model author has used InceptionResNetV2 model with output layer as -

out=dense (1, activation='sigmoid') (x).

Similarly, for the multi-label classification author has used the same InceptionResNetV2 model with output layer as -

Out=dense (4, activation='sigmoid') (x).

For better results author used test time augmentation for better results. After few epochs we observed that binary model gave accuracy 94 and recall 96 and multi-label model gave accuracy of 96.

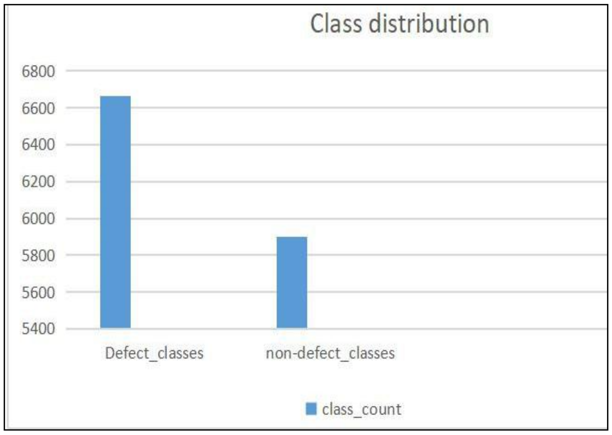

Figure 2. Binary Classification

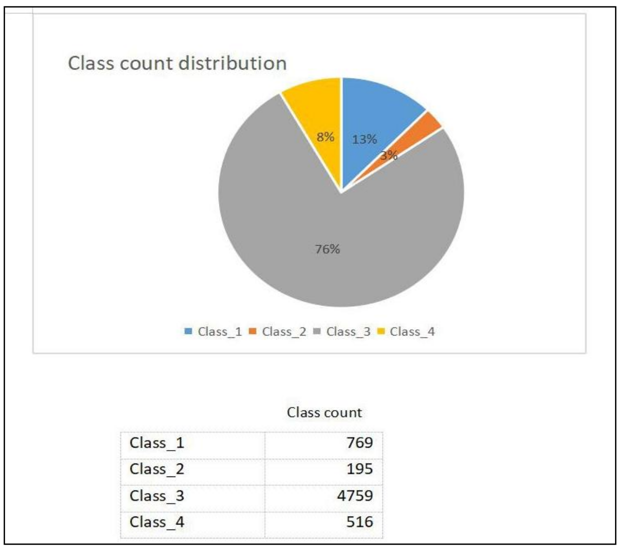

Figure 3. Multi-Label Classification

4.3. Segmentation

The classified image became the input of segmentation model and the RLE's provided in train data were converted to masks to get fit in train data. Four different segmentation model was built because one image belongs to multiple classes so it became easy to predict exact location of defect. The model gave us good results with dice coefficient (F1 score) of 92 after 25 to 30 epochs. For predicting the pixel regions of defected images run length encoders were used which was given by Kaggle [13] to reduce file submission size.

5. Conclusion

There were 12568 train images and 1801 test images which we categorized as defective and non- defective after which the defective images were classified into four different classes. At last, our binary model gave us the accuracy of 94 and the multi-label classification model gave the accuracy of 96. The results can be improved either by using better data augmentation techniques or by using a better pipeline strategy. Moreover, our technique is light weighted, which means that it does not comprise too many parameters and does not require too many resources to train. As an effect, it will be easy to be taken into practice.

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