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Steel Surface Defect Detection using the RetinaNet Detection Model

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Abstract

Some surface defects make the weak quality of steel materials. To limit these defects, we advocate a one-stage detector model RetinaNet among diverse detection algorithms in deep learning. There are several backbones in the RetinaNet model. We acknowledged two backbones, which are ResNet50 and VGG19. To validate our model, we compared and analyzed several traditional models, one-stage models like YOLO and SSD models and two-stage models like Faster-RCNN, EDDN, and Xception models, with simulations based on steel individual classes. We also performed the correlation of the time factor between one-stage and two-stage models. Comparative analysis shows that the proposed model achieves excellent results on the dataset of the Northeastern University surface defect detection dataset. We would like to work on different backbones to check the efficiency of the model for real world, increasing the datasets through augmentation and focus on improving our limitation.

Keywords: *Defect Detection, Deep Learning, Steel Defect Detection, RetinaNet model, One-Stage Detector*

1. Introduction

Detecting a defect in a product or materials is a crucial task as it can change the functionality, effectiveness, and quality of the product. If the defects are not analyzed and neglected, they can lead to huge disasters in product making and it will affect the industry reputation by deploying the defective material. Defect detection is a method that facilitates exploring and diminishing the defects in a product and assisting in the enhancement of the quality of the product. The defect detection method is an important step in quality production. The approach will help in good quality products, excellent accuracy, customer satisfaction, increase productivity, and overall industrial reputation. Defect detection can be persuaded in any sector whether its software industry or metal industry or machinery industry.

Today the steel world industry is growing at a rapid speed. With the increasing demand for steel materials and with the fast production of steel the major concern which bothers is the quality of the steel produced. The increase in competition between the steel industries as everyone wants to grab the market has led to the degradation of steel manufacturing.

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During the manufacturing of steel is it deteriorated to enormous different defects. Every production company requires a good quality of steel for its products. The metal industries require defect detection approaches to analyze the issue of the defects occurring on the steel surface and of what type. Manual defect detection has been a very tedious task as there can be human eye error possible but the automatic process of machines can lead to overcoming this human error. One of the upcoming technologies which can easily administer the manual process is Deep learning. Deep learning is a benefit for this industry. Deep learning technology helps in resolving the steel defect detection. Various deep learning approaches have been introduced for defect detection. Some of the approaches we will be discussing in the coming section.

Deep learning is a more detailed and deeper sub-field of machine learning, which is a subset of artificial intelligence. Deep learning is a mirror-like functioning of the human brain which helps in detecting objects, defects, language translation, speech recognition, and many more. It can be both supervised and unsupervised depending upon the data availability. For the technique to be supervised an enormous amount of labeled dataset is required for training of the model. In the case of unsupervised learning, it happens when there is data scarcity and data is unlabeled for the training of the model. Deep learning has revolutionized various sectors because of its learning and computing ability. The most popular model used for image recognition, object, and defect detection is Convolutional Neural Network. This network settles the concerns of extracting features separately first and then doing the detection by combines the feature extraction and detection in a single model. Various algorithms come under this neural network. Some algorithms will be used in our model for feature extraction and detection.

In this paper, we have proposed a one-stage defect detector algorithm for the classification and detection of defects on steel surfaces. We compared our model with the other architectures to evaluate individual defect detection.

The paper is organized as follows. In section 2 we discussed the related work on traditional and state-of-the-art methods, followed by the methodology explaining the detection model in section 3. In section 4 experiment evaluation is illustrated. Finally, the paper is concluded in the last section.

2. Related Works

2.1 Traditional Methods

The traditional methods for image processing are broadly classified into four categories: structural-based approach, statistical-based approach, filter-based approach and model-based approach. The structural-based approach focuses on the characteristics and the skeleton of an image on spatial domain. The texture elements can be single pixels, line segments or regions of gray-scale. The methods included in this approach are for edge detection, texture detection etc. In paper [1], they discuss about the edge detection method for fault defect of the material. In paper[2] the authors discuss a skeleton-based structural approach for defect detection of the textured surface images. In paper[3, 4], the researchers discuss about the morphological method, a structural approach for feature extraction by isolating the defects from the background and some using the additional backlight technique[5] for defect detection. The statistical based technique is based on the distribution of pixel values on a given image. Various techniques are included from low to high level statistics histograms, thresholding, concurrence matrix, local binary pattern(LBP), autocorrelation and others. In paper[6] the authors propose two threshold based Otsu method, one is contrast-adjusted and another is contrast-adjusted median for defect detection on aluminum surface. One of the well-known statistical methods is gray level co-occurrence matrix (GLCM). It is a matrix generated at the given offset of an image projecting the co-occurring gray scale values. Through these matrices, it extracts features help for detection. Several researchers in papers[7, 8, 9, 10, 11] describes the employment of this method for defect detection. The histogram of oriented gradient(HOG), a feature detection method is employed for object detection in image processing field. For particular offset of an image, the gradient's orientation and magnitude benefits in the generation of histograms, which further helps in the detecting the defect area. Various studies in papers[4, 8, 12, 13, 14] demonstrated the utilization of HOG approach for feature extraction of defects. LBP is an efficient and low cost computational operator for defect detection. Each pixels of an image is labeled by thresholding its neighboring pixels and compute the result as binary values. Many researchers implemented this approach for defect detection applications on distinctive materials[11, 15, 16, 17, 18]. The filter based methods are the initial level approaches required for filtering the features detected by various extraction methods with Fourier transform [19, 20, 21]. Gabor filters eliminate the drawbacks of Fourier transform but combining the spatial and frequency domain[22]. The wavelet transform involves small waves with limited period and differing frequency[23].

Finally, the model-based approaches for defect detection categorized in three, markov random field is a combination of structural and statistical knowledge of context[24]. The fractal model describes the similar feature of the defects on different scales[25]. The autoregressive model focuses on the pixel linear dependency for feature extraction for defect detection[26].

In the real world applications the above traditional approaches are quite challenging due to numerous factors like noise, illumination, environmental effect etc. due to which the parametric setting are changed frequently making it incompatible for real-time function. It further leads to low accuracy and inefficient model performance for defect detection.

2.2 Deep Learning Methods

To overcome the shortcomings of the traditional approach, there are some researchs using deep learning methods. The deep learning architecture consists of classification and regression parts in one model. There are numerous deep learning models proposed which was depending on the user requirements. The authors of the paper[27] introduce a Single Shot Multibox Detector(SDD) with VGG-16 as base model for end-to- end defect detection on the steel surface. The hard negative mining method is introduced to reduce imbalance problem. The paper [28] discusses about Xception, CNN architecture for defect detection. The model performs two-step classification, first is binary classification for the presence of defects and second is multi-label classification to identify the category of the defect. The paper fails to demonstrate the localization of the defects. Varied CNN architectures pre-trained on COCO and ImageNet dataset like VGG [29], Overfeat network [30], ResNet [31] are implemented for steel surface defect detection. Researchers introduce a defect detection system for the quality analysis of steel strip and plate surface[32]. In other studie [33], a defect detection network with ResNet50 as the base model, multilevel feature fusion to assemble all the features and RPN for region of interest is proposed. The model is compared with other deep learning models. The detection accuracy is less compared to classification. The use of AlexNet as the base network for transfer learning and a customized CNN network for the analysis of defects on steel surface provides decent accuracy[34]. In the paper[35], the authors introduce an improvised R-CNN model and feature pyramid network for steel defect detection. And thare are various state-of-the-art methods including SSD[36], You Only Look Once V2 (YOLOV2) [37], YOLO-V3 [38]. And faster R-CNN [39] also contributed in the steel surface defect detection.

3. Methodology

In this study, we will be using a one-stage detector for detecting defects on the steel surface. This method will focus on detecting six defects on the steel surface. But before understanding the architecture of the model we will first understand what a one-stage detector is and why it is different from a two-stage detector.

3.1 One-Stage versus Two-Stage Detector

Deep Learning models have to be classified broadly in two for detecting an object. One-stage object detection is a process in which the object is detected and classified in one go. This detector process does not require an additional regional proposal stage as it directly does the detection process on the dataset available. This process is simple and faster than the two-stage detector. For the time crucial situation this detector works the best. The one-stage models are the good preference for real-time applications for their time feature. But the main shortcoming of this detector is the inadequate accuracy. Some of the models working on this concept are YOLO, YOLOv2, YOLOv3, SSD, RetinaNet[40], and RefineDet. The two-stage object detection process works in two stages. In the first stage with the help of the regional proposal stage (region of interest), the regions are decided for detection in an input image. In the second stage, the discovered regions are then classified with the help of a classification algorithm. This detector contributes desirable accuracy for the detection. The fallout of this process is that it is very slow, and makes it difficult to apply on real-time applications. The models working on this concept are R-CNN, Fast R-CNN, Faster R-CNN, Mask R-CNN, and DenseNet.

3.2 Our Defect Detection Model

In our defect detection model for real-time applications, we use RetinaNet, which is one of the one-stage detectors. We compare the RetinaNet model and with other state-of-the-art detectors in terms of good speed and acceptable accuracy. The other state-of-the-art detectors has a simple architecture. In our model, we comprise RetinaNet architecture with a backbone network known as Feature Pyramid Network (FPN)[41-43], shown in Fig.1. On top of the ResNet model, we use a backbone network. The FPN's main feature is to compute the feature maps through the convolution of an input image. Our RetinaNet architecture consists of two subnetworks; one is the classification part which classify objects provided by the FPN. The second one is the regression part which sets the boundary of box on the outputs from FPN.

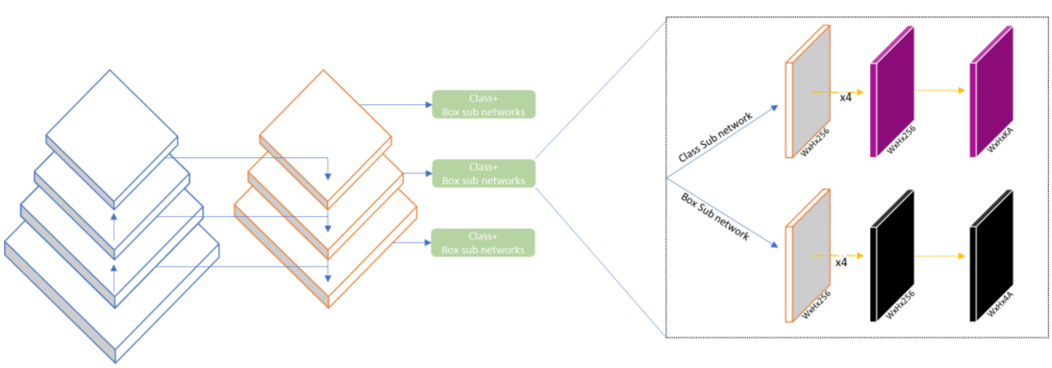


Figure 1. RetinaNet architecture

The FPN consists of two pathways; bottom-up and top-down. Both these pathways are connected in a lateral connection. The FPN takes as input in arbitrary size, and then produces feature maps with proportional size at different levels, because of its fully convolutional nature. The different levels provide the hard features which difficult to detect defects. Also we can predict objects and their classes with the output feature maps of FPN. And we can classify the defective state of final images with the bounding box and respective class.

4. Experiments

The experiment is conducted on the NEU dataset, which will be described shortly. We will be considering ResNet50 and VGG19 as the backbone for RetinaNet. The following section contains the description of the dataset used, the performance analysis of both the backbones on basis of individual defects, the loss graphs of both the backbones which include loss, classification loss and, regression loss, comparison of our method with the deep learning methods and traditional methods.

4.1 Datasets

This study will consider the Northeastern University (NEU) surface defect detection dataset [5]. This dataset is a collection of defects on hot-rolled steel strip, which consist of six defects, that is, Pitted Surface (PS) Inclusion (In), Patches (P), Rolled-in_scale (Rs) and, Crazing (Cr). This dataset includes 300 image samples for each defect respectively.

• Pitted Surface: It is also known as pits, which are small in size but deep. It looks corrosive on the surface which can only be removed by scraping. This is formed by the chemical reaction taking place between oxide and metal oxide. It compromises the strength of the material as it penetrates deeply.

• Inclusion: It is a non-metal particle that is present on steel surface which is created because of the contamination, chemical and, physical actions performed during the melting and pouring process of the steel. It can cause quality issues like hard spots on the surface, loss of strength of the material, affect the flow consistency of the material

• Patches: This defect is blocked out at some part of the steel surface, which makes the tone of the steel surface uneven. This happens because of the fault in the pickling process, the oxides are not eliminated completely

• Rolled-in scale: This defect occurs during the rolling process of the metal when a mixture of flaky iron oxides also known as mill scale when rolled in the metal. This affects the uniformity of the steel surface and the quality deteriorates.

• Crazing: These defects form cracks on the steel surface due to high tension on the surface. It’s a collection of fine cracks. If the stress increases on the surface chances are that the crack will increase and break. This affects the strength of the material.

4.2 Performance Evaluation

We have performed the test on the above dataset considering the two different backbones of RetinaNet. One is ResNet50 and the other one is VGG19. We will focus on individual defect detection. Table 1. and Table 2.

exhibits the average precision (AP) of individual defects

Table 1. Average precision of individual classes of defects on ResNet50 backbone

AP ON RESNET50 BACKBONE

PITTED SURFACE	0.835
INCLUSION	0.557
PATCHES	0.883
ROLLED-IN_SCALE	0.438
CRAZING	0.425

Table 2. Average precision of individual classes of defects on VGG19 backbone

AP OF VGG19 BACKBONE

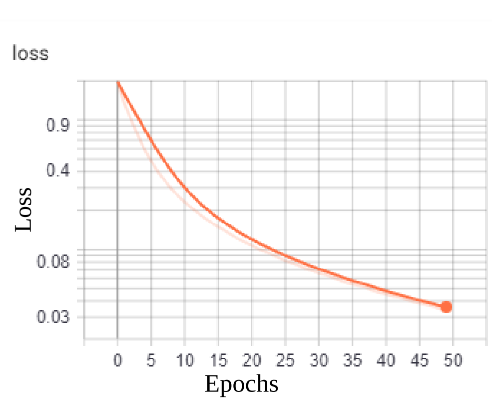
PITTED SURFACE	0.848
INCLUSION	0.611
PATCHES	0.925
ROLLED-IN_SCALE	0.537
CRAZING	0.474

4.3 Losses Evaluation

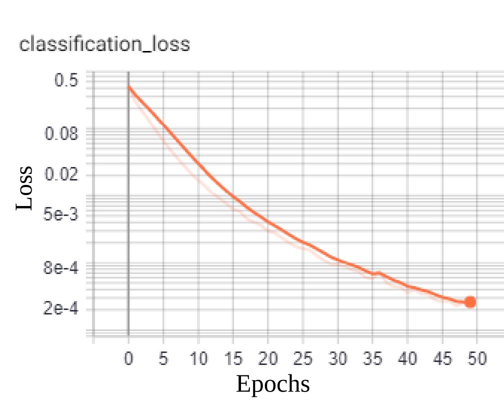
We have evaluated the loss factor on both the backbones.

4.3.1 Loss Graphs of ResNet50

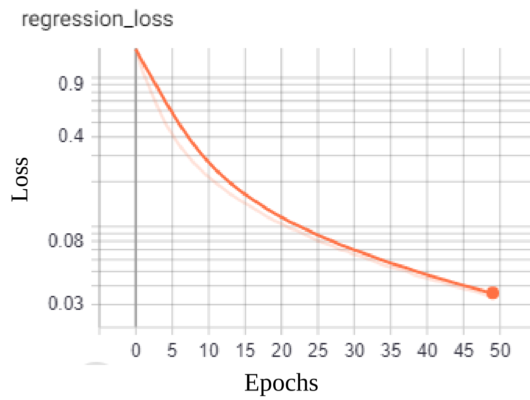
The following Figure 2. shows the loss graph, classification loss graph and, regression loss graph of ResNet50. The evaluated losses values of classification loss is 0.00026, regression loss is 0.03451 and loss is 0.03477 respectively.



(a)



(b)

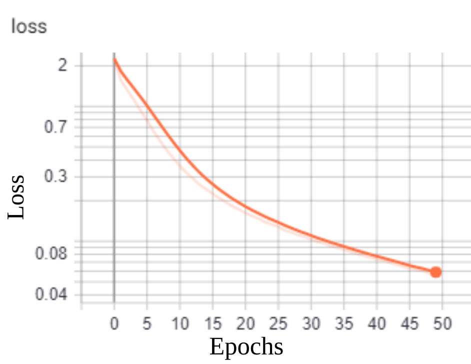


(c)

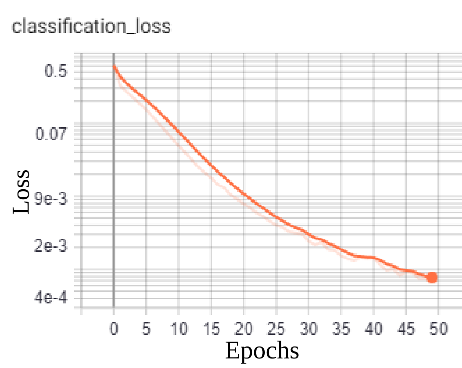
Figure 2. (a) Loss (b) Classification loss (c) Regression loss graphs for ResNet50 backbone

4.3.2 Loss Graphs of VGG19

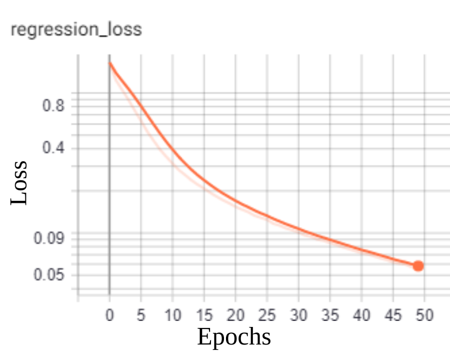
The following Figure 3. shows the loss graph, classification loss graph and, regression loss graph of VGG19. The evaluated losses values of classification loss is 0.00070, regression loss is 0.05548 and loss is 0.05619 respectively.



(a)



(b)



(c)

Figure 3. (a) Loss (b) Classification loss (c) Regression loss graphs for VGG19 backbone

4.4 Comparison of Accuracy with Deep Learning Methods

We have done a comparison between our method and the state-of-the-art methods which are SSD, Faster-RCNN, YOLO-V2, YOLO-V3, EDDN and, Xception, The Table 3. shows how our method with both ResNet50 and VGG19 backbone performed well for defects like patches, crazing and pitted surface compared to the other methods. We knew that our method have good precision for pitted surface defects, patches defects, and crazing defects. But our method have same like or low precision for inclusion defects and rolled in scale defects.

Table 3. Comparison of average precision with deep learning models

DEFECTS	AVERAGE PRECISION							
	SSD	Faster-RCNN	YOLO-V2	YOLO-V3	EDDN	Xception	Our Method (ResNet50)	Our Method (VGG19)
PITTED SURFACE	0.839	0.815	0.454	0.239	0.851	0.75	0.835	0.848
INCLUSION	0.796	0.794	0.592	0.580	0.763	0.50	0.557	0.611
PATCHES	0.839	0.853	0.774	0.772	0.863	0.67	0.883	0.925
ROLLED-IN_SCALE	0.621	0.545	0.246	0.335	0.581	N/A	0.438	0.537
CRAZING	0.411	0.374	0.211	0.221	0.417	N/A	0.425	0.474

4.5 Comparison of Accuracy with Traditional Methods

We have done a comparison between our method and the traditional methods which are HOG and LBP with two classifiers Neighbor classifier (NNC) and Support vector machine (SVM). The Table 4. shows our method with both ResNet50 and VGG19 backbone outperforms the other traditional models on all defects. We knew that our method have good precision for pitted surface defects, inclusion defects, patches defects, rolled in scale defects, and crazing defects. Especially, our method classified with 0.848 and 0.925 accuracy for pitted surface defects and patches defects.

Table 4. Comparison of average precision with traditional methods

DEFECTS	HOG+NNC	HOG+SVM	LBP+NNC	LBP+SVM	OUR METHOD (RESNET50)	OUR METHOD (VGG19)
PITTED SURFACE	0.438	0.328	0.446	0.515	0.835	0.848
INCLUSION	0.576	0.580	0.412	0.378	0.557	0.611
PATCHES	0.612	0.630	0.538	0.601	0.883	0.925
ROLLED-IN_SCALE	0.358	0.330	0.237	0.330	0.438	0.537
CRAZING	0.400	0.412	0.321	0.335	0.425	0.474

4.6 Comparison of Time Factor between One-Stage and Two-Stage Detectors

In Table 5. we summarized the time factor between the one-stage and two-stage detectors. From the Table 5. we can analyze that, Firstly the one-stage detectors are faster compared to the two-stage detectors and secondly among the one-stage detector, though the YOLO-v2 seems to be fast, RetinaNet is way ahead of accuracy with YOLO-V2 so the time factor of RetinaNet is considerable in real-time application. RetinaNet is more efficient, time-saving and, more accurate among the one-stage detectors.

Table 5. Comparison of time between two-stage and one-stage detectors

DETECTOR MODELS	TIME(MS)
TWO-STAGE	
R-FCN [26]	85
FASTER-RCNN	172
ONE-STAGE	
YOLO-V2	25
SSD	125
YOLO-V3	93.5
EDDN	118
RETINANET	73

5. Conclusion

In this paper, we studied steel defect detection using the RetinaNet model, a one-stage detector. We evaluated the average precision of individual classes of defects on the given dataset and generated the losses of two backbones, that is, ResNet50 and VGG19. We did a comparative analysis of our work with state-of-the-art methods and traditional methods. From the analysis, we can observe that in most of the classes of defects our work performed better. We also did the comparison between the one-stage and two-stage detectors based on time. We also performed the correlation of the time factor between one-stage and two-stage models. Comparative analysis shows that the proposed model achieves excellent results on the dataset of the Northeastern University surface defect detection dataset. Though there are some limitations like we have only considered some defect classes. In the future, we would like to work on different backbones to check the efficiency of the model for real world, increase the datasets through augmentation and focus on improving our limitation.

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