Classification of Surface Defects using Semi-Supervised Deep Learning

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Introduction

In manufacturing, quality control is a process that ensures customers receive defect-free products. Defect identification is commonly performed manually by trained workers by visual inspection. But it is subjective, unreliable and time consuming. To overcome this, vision based Automatic surface inspection (ASI) methods are proposed, as they are fast, highly accurate and significantly reduces labor intensity. In this work, a Convolutional Neural Network based semi-supervised learning approach is proposed for the recognition of surface defects as it requires little amount of labeled data compared to fully supervised approaches.

Our contribution of this work are:

- We propose a semi-supervised deep learning approach for the classification of surface defects.
- We propose a sample weighting strategy based on how well each unlabeled sample is predicted.

Our proposed approach achieves State-of-the-art results on three public datasets with limited amount of training data.

Proposed Methodology

Loss Function

No. of classes

$$\mathcal{L} = -\sum_{c=1}^{C}\left[\underbrace{\sum_{i\in\mathcal{D}_L} y_{ic}\log p_{ic}}_{\text{Labeled data}} + \underbrace{\sum_{i\in\mathcal{D}_U} w_i\,\hat{y}_{ic}\log p_{ic}}_{\text{Unlabeled data}}\right]$$

One-hot representation of image *i* belonging to class *c*

Pseudo-label of image *i*

Weight for image *i*

There are multiple ways this weight can be determined.

p_{ic} - Probability of image *i* belonging to the class *c*.

The proposed cross entropy based loss function is minimized to learn the parameters of the CNN. This loss function contains two terms, the first one is based on the labeled data (D_L), and the second one is based on the unlabeled data (D_U).

Weighting Schemes

- Equal weights for all the unlabeled images (*We*)
  - Problem: All the samples are considered, regardless of their confidence in prediction.
- Selection of a subset of unlabeled images based on prediction probability (*Ws*)
  - Problem: All the samples above a threshold are only considered.
- Soft-weighting based on probability (*Wp*)
  - Problem: Soft weights based on the probabilities.
- Weighting based on a margin criteria (*Wm*) (Proposed)

$$w_i = \frac{1}{1+e^{-\beta(d-t)}}$$

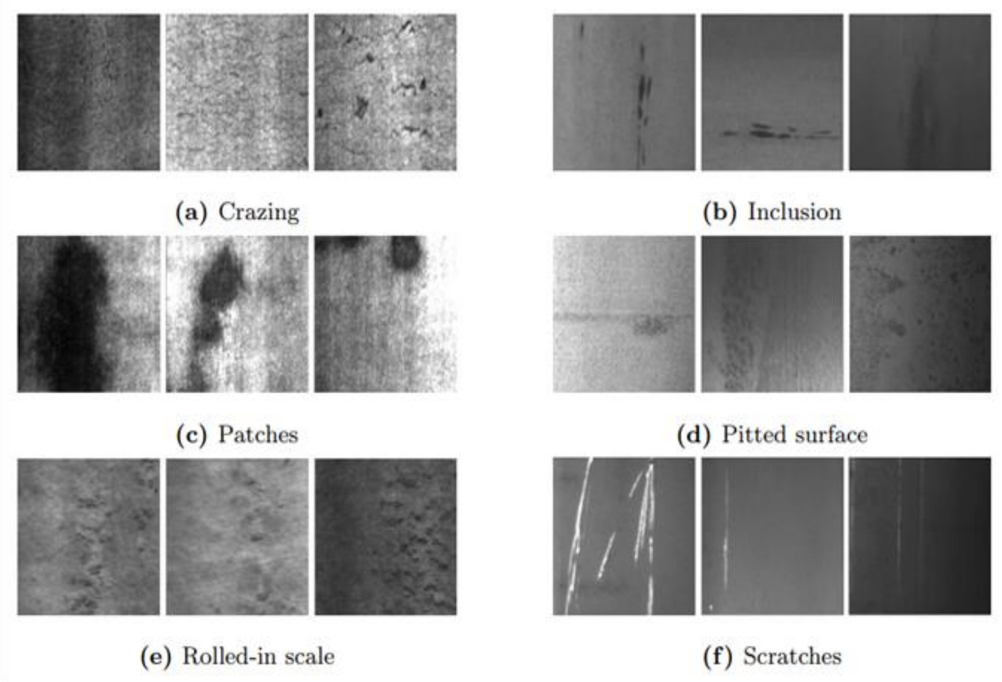
where, $d = \hat{p}_i - \hat{p}'_i$

β - softness of the weight
t - soft threshold parameter.
$\hat{p}_i$ - maximum probability for image *i*
$\hat{p}'_i$ - second maximum probability for image *i*

- Soft weights based on how well each sample is classified.

Datasets

1. **Northeastern University dataset (NEU)** [1]
   - six steel surface defects, 1800 images in total
2. **KolektorSDD dataset** [2]
   - 399 images of plastic electronics commutators
   - Defective vs non-defective
3. **Surface textures dataset** [3]
   - 8,674 images from 64 classes



NEU dataset

Experiments and Results

Comparison of fully supervised (FS) vs. semi-supervised (SS) approaches on different datasets

Dataset	Backbone	FS/SS	Overall accuracy (%) for different number of training samples per class				
			5%	10%	25%	50%	100%
NEU	Resnet-10	FS	91.69 ± 1.52	97.00 ± 0.09	99.45 ± 0.26	99.67 ± 0.17	99.86 ± 0.11
		SS	**98.34 ± 0.36**	**99.50 ± 0.12**	**99.75 ± 0:14**	**99.82 ± 0.05**	-
Kolektor SDD	Resnet-10	FS	79.94 ± 4.37	85.59 ± 1.13	100 ± 0.00	100 ± 0.00	100 ± 0.00
		SS	**85.10 ± 2.24**	**88.60 ± 0.69**	**100 ± 0.00**	**100 ± 0.00**	-
Textures	Resnet-18	FS	86.71 ± 0.45	93.58 ± 0.38	96.62 ± 0.32	99.09 ± 0.05	99.52 ± 0.13
		SS	**89.52 ± 0.48**	**95.33 ± 0.28**	**98.60 ± 0.20**	**99.50 ± 0.01**	-

In this experiment, we randomly select s% of images (s is varied from 5% to 100%).
FS Approach: we used s% of labeled samples only from the training set for training.
SS Approach: In addition to the s% of labeled samples, the remaining images from the training set are used as unlabeled samples for training.

Semi-supervised learning gives significant improvements over fully supervised learning on all the three datasets.

- On the **NEU** dataset, our approach achieves the state-of-the-art results with **10%** of labeled training data.
- On the **KolektorSDD** dataset, our approach achieves the state-of-the-art results with **25%** of labeled training data.
- In addition, on the **Surface Textures dataset**, we achieve the state-of-the-art results with only **50%** of labeled training data.

Comparison of the weighting schemes on the NEU dataset

Weighting Schemes	Ws	Wp	Wm
Accuracy	97:10 ± 0.84	97:50 ± 0:78	**98:34 ± 0:36**

Comparison with the state-of-the-art approaches on the Kolektor SDD dataset

Method	AP for different number of positive training samples		
	5	10	33
Segmentation based approaches which use both image and pixel level labels for training			
Jakob et. al. [11]	96.71	99.31	100
Tabernik et. al. [12]	95.80	98.80	99.00
Cognex ViDi (commercial software) [12]	89.20	95.60	99.00
Image level labels only			
Xu et. al. [13]	-	98.0	99.50
Ours	88.60 ± 0.69	**100 ± 0.00**	**100 ± 0.00**

Comparison with the state-of-the-art approaches on the Surface Textures dataset

Method	Accuracy for different percentage of labeled training images		
	25%	50%	100%
Huang et. al. [14]	-	-	99.33
Ours	**98.60 ± 0.20**	**99.50 ± 0.01**	**99.52 ± 0.13**

Comparison with the state-of-the-art approaches on the NEU dataset

Methods	Overall accuracy (%) for different number of training samples per class				
	9 (5%)	18 (10%)	45 (25%)	90 (50%)	180 (100%)
Supervised learning					
Zhou et. al.[4]	-	-	78.09	80.00	86.64
Li et. al. [5]	-	-	82.81	85.39	95.00
Ren et. al.[6]	-	-	-	90.88	92.04
He et. al. (CAE-SGAN) [7]	-	-	-	-	98.96
He et. al. (cDCGAN) [8]	-	-	-	-	99.56
Wang et. al. (MMGCN) [9]	-	-	-	-	99.72
Ours	**91.69 ± 1.52**	**97.00 ± 0.09**	**99.45 ± 0.26**	**99.67 ± 0.17**	**99.86 ± 0:11**
Semi-supervised learning					
He et. al. (CAE-SGAN) [7]	-	-	85.83	94.87	-
He et al. (cDCGAN) [8]	-	-	89.58	96.06	-
Gao et. al. (PLCNN) [10]	-	-	90.7*	-	-
Wang et. al. (MMGCN) [9]	-	-	98.06	98.75	-
Ours	**98.54 ± 0.36**	**99.50 ± 0.12**	**99.75 ± 0.14**	**99.82 ± 0.05**	-

* Note: PLCNN[10] is trained with 50 samples per class

Conclusion

- This work proposed a simple and efficient semi-supervised deep learning approach for the classification of surface defects.
- Our approach is not specific to a particular CNN architecture, and any CNN architecture can be easily incorporated.
- The proposed semi-supervised learning approach performs better than its fully-supervised version.
- Our approach achieves the state-of-the-art results on all of these datasets with relatively low amount of labeled training data compared to other approaches.

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