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A graph-based two-stage classification network for mobile screen defect inspection

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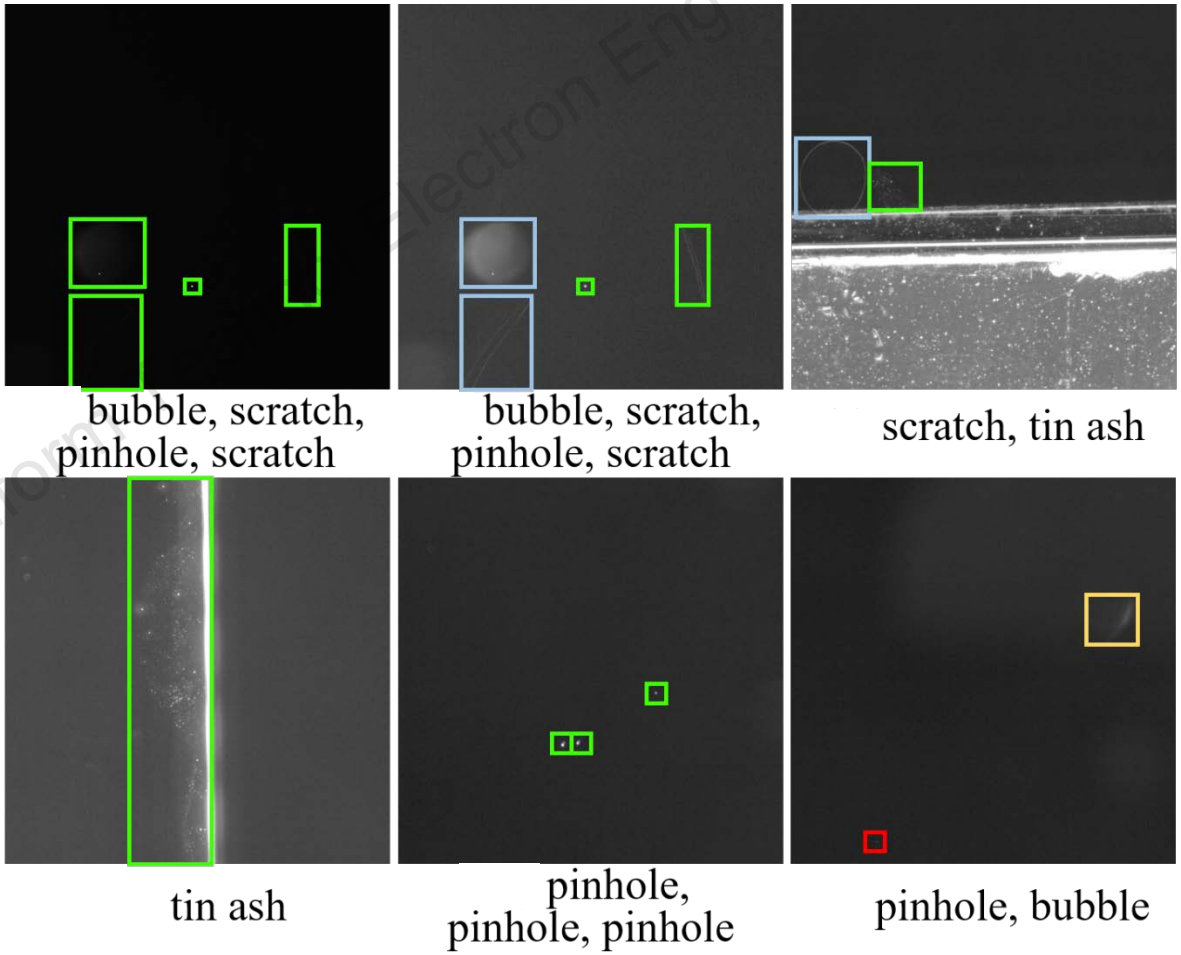
Key words: Graph-based methods; Multi-label classification; Mobile screen defects; Neural networks

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Motivation

- Accurate and efficient defect inspection is significant for mobile phone screen industrial processes.
- There are some challenging issues brought by the characteristics of screen defects.
  - The problem of interclass similarity and intraclass variation (as shown in blue boxes)
  - The difficulty in distinguishing low contrast, tiny-sized, or incomplete defects (as shown in red box, red box, yellow box)
  - The modeling of category dependencies for multi-label images



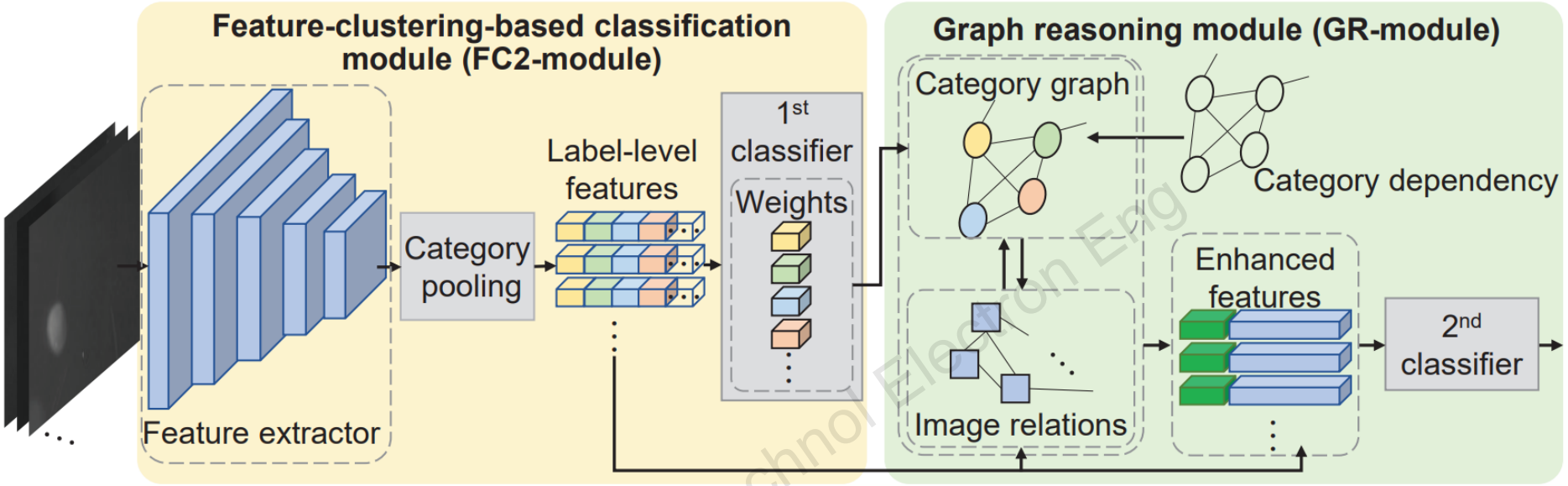
Samples of mobile screen defects

Main idea

- A two-stage defect inspection network is proposed. which consists of two components, i.e., a feature-clustering-based classification module (FC2-module) and a graph reasoning module (GR-module).
- The graph in the GR-module enhances the image features with the help of category features to increase the interclass distance and the intraclass correlation in the feature space.
- Image-wise relations are applied to improve features of images that have low contrast, tiny-sized, or incomplete defects. When humans are not sure about the objects in the image being viewed, they refer to other images in which similar objects occur.
- We model the category dependencies using the graph convolution network (GCN) and the co-occurrence patterns of defects.

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Method



The proposed two-stage network

Pipeline:

(1) The input images are sent to the feature-clustering-based classification module (FC2-module) to obtain label-level features and distilling weights.

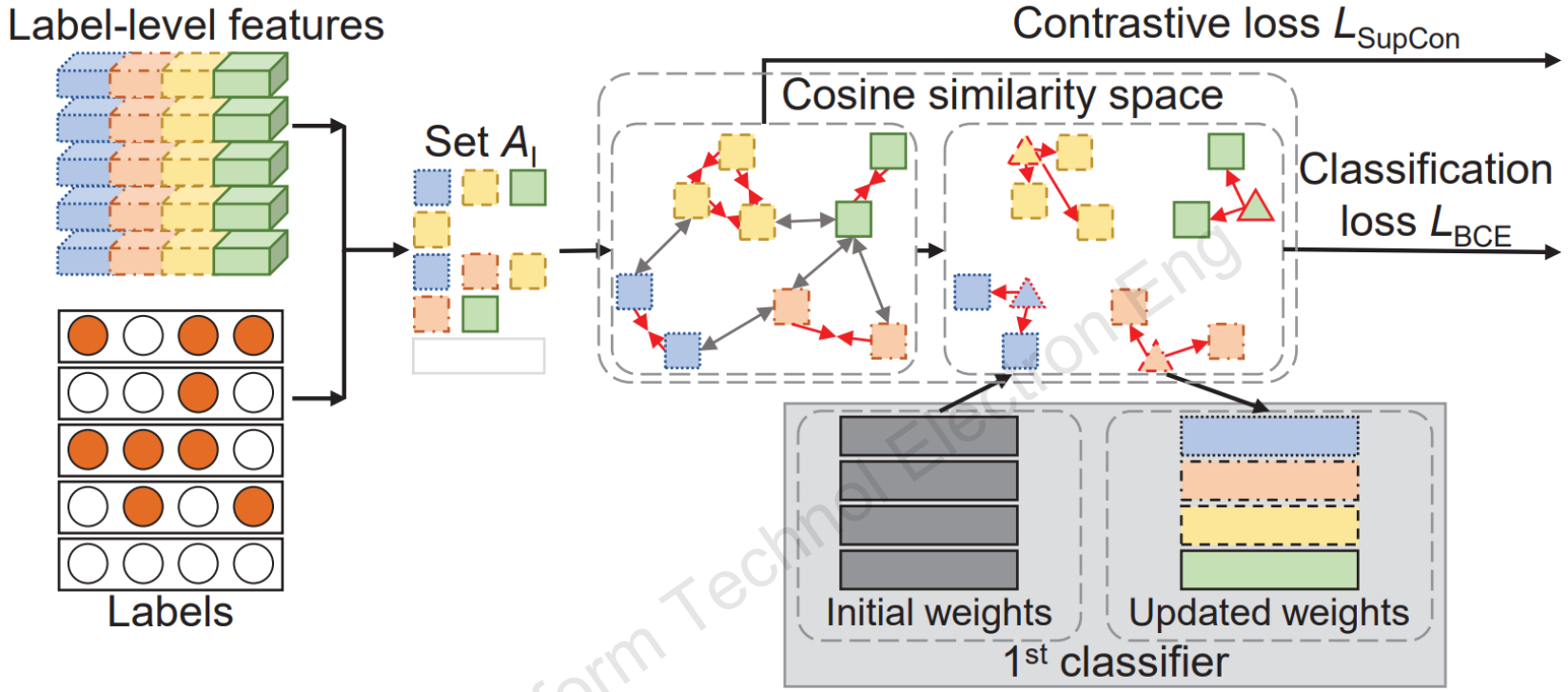
(2) Features and weights are fed into the graph reasoning module (GR-module) to enhance features.

(3) Enhanced features are used to improve the classification performance.

Key point:

Based on graph, the GR-module exploits category-wise dependency, image-wise relations, and interactions between them. By doing so, the GR-module can incorporate category semantics and image relations to guide enhancement of image features.

Method (Cont'd)



The pipeline of updating the weights of the first classifier

Design reason :

- To make graph better promote the model's performance, we use the distilling weights of the first classifier as the representations of category nodes.
- To make the weights of the classifier learn enough information about each defect category, the pipeline of updating the weights contains two parts:
  (1) contrastive learning, improved based on multi-label characteristics, which gathers label-level features with the same label;
  (2) a classifier that makes the weights represent the overall features of each cluster.

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Constructed dataset

Table 1 Number of patches of each category in the training, validation, and testing sets

Category	Number of patches in the training set	Number of patches in the validation set	Number of patches in the testing set
Bubble	91	21	33
Pinhole	1514	229	344
Scratch	1010	235	228
Tin ash	726	194	130
Defect-free	540	123	111
Total patches	2520	503	578

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- The table shows the number of patches of each category in the training, validation, and testing sets.
- It is constructed by collecting image data from the real industrial pipeline.

Major results

Table 2 Comparisons with state-of-the-art methods on a multi-label screen defect classification task

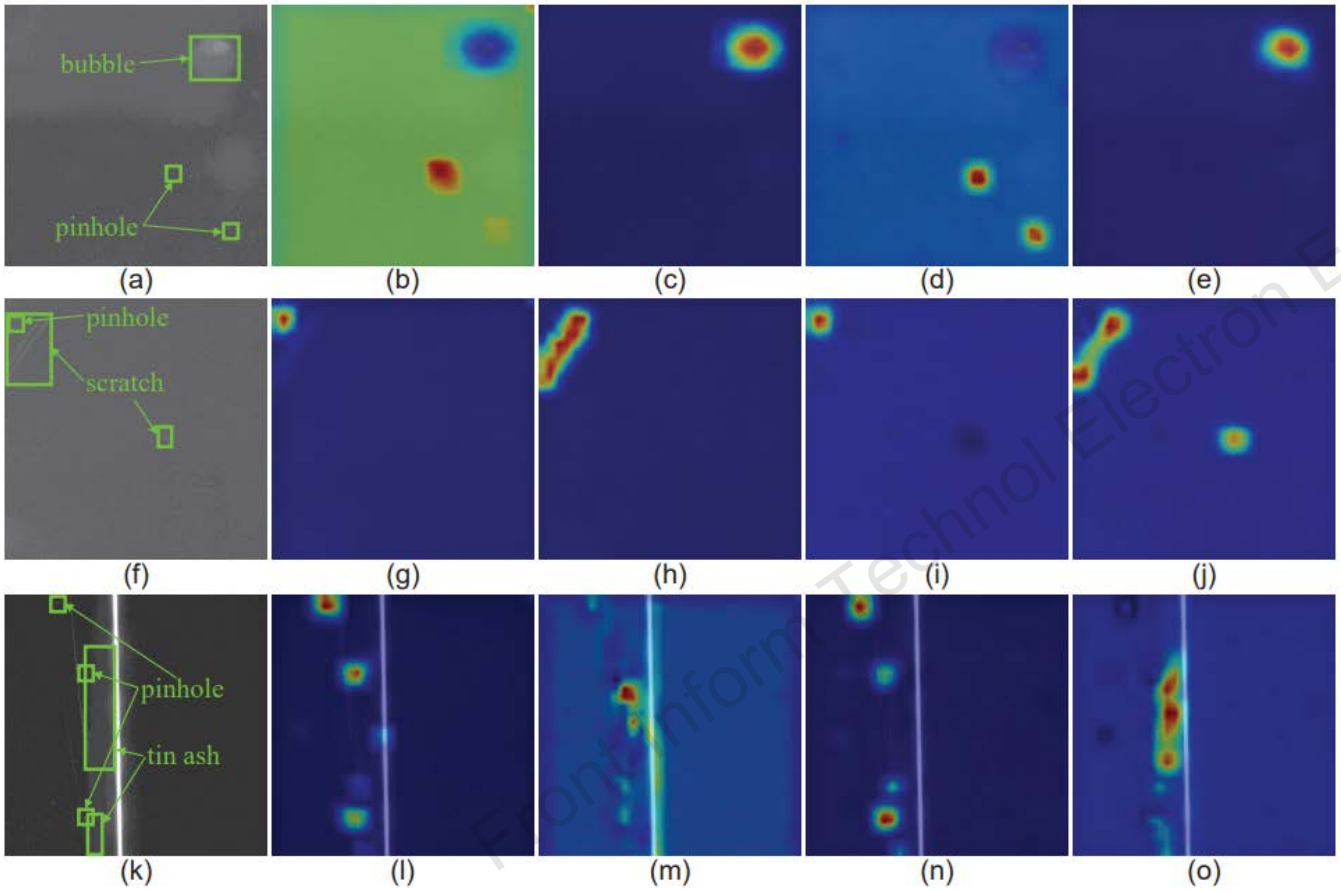
Method	Accuracy	Precision	Recall	*F*-measure
ResNet-50	0.952	0.966	0.919	0.942
VGG-16	0.967	0.963	0.827	0.890
Inception-v3	0.971	0.963	0.953	0.958
KSSNet	0.953	0.828	0.713	0.767
TDRG	0.972	0.963	0.959	0.961
SewerMl	0.887	0.820	0.727	0.771
Ours	**0.977**	**0.975**	**0.970**	**0.973**

The results in bold are the highest

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- Our approach achieves the highest accuracy (97.7%), precision (97.5%), recall (97.0%), and *F*-measure (97.3%) on the mobile screen defect dataset.
- Compared with the second place of each metric, our model outperforms with a margin of 0.5% on accuracy, 0.9% on precision, 1.1% on recall, and 1.2% on *F*-measure.
- These results prove that the proposed method is feasible.

Major results: Network visualization



Visualization for feature maps with a class activation map (CAM): the second and third columns show visualization results of ResNet-50, and the fourth and fifth columns exhibit those of our approach

- Figs. (b) and (d): the maps of our approach can highlight regions of tiny-sized defects.
- Figs. (h) and (j): the maps of our approach can highlight regions of low contrast and incomplete defects.
- Figs. (m) and (o): the maps of our approach can highlight illegible regions caused by the characteristic of interclass similarity and intraclass variation.

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Major results: Generalization performance

Table 9 Comparisons with the state-of-the-art methods on the steel surface defect dataset

Method	Accuracy	Precision	Recall	F-measure
ResNet-50	**0.982**	0.915	0.877	0.896
VGG-16	0.974	0.850	0.848	0.849
Inception-v3	0.979	0.912	**0.928**	0.920
KSSNet	0.953	0.839	0.617	0.711
TDRG	0.978	0.896	0.853	0.874
SewerMl	0.954	0.813	0.707	0.756
Ours	**0.982**	**0.960**	0.885	**0.921**

The results in bold are the highest

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- Dataset: created by Severstal and is multi-label.
- Compared to other methods, our model achieves the best results on almost all metrics, which proves that it has good generalization capability.

Conclusions

- Given the characteristics of mobile screen defect data from the real industrial pipelines and the difficulties in recognizing them, we proposed a two-stage defect inspection framework, consisting of the FC2-module and the GR-module.
- Our approach is mainly designed for three problems: (1) the problem of interclass similarity and intraclass variation, (2) the difficulty in distinguishing low contrast, tiny-sized, or incomplete defects, and (3) the modeling of category dependencies for multi-label images.
- The experimental results on the mobile screen defect dataset showed that our model has better defect inspection performances: 97.7% accuracy and 97.3% *F*-measure.
- Our approach can detect illegible defects and has good generalization capability.

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