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



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

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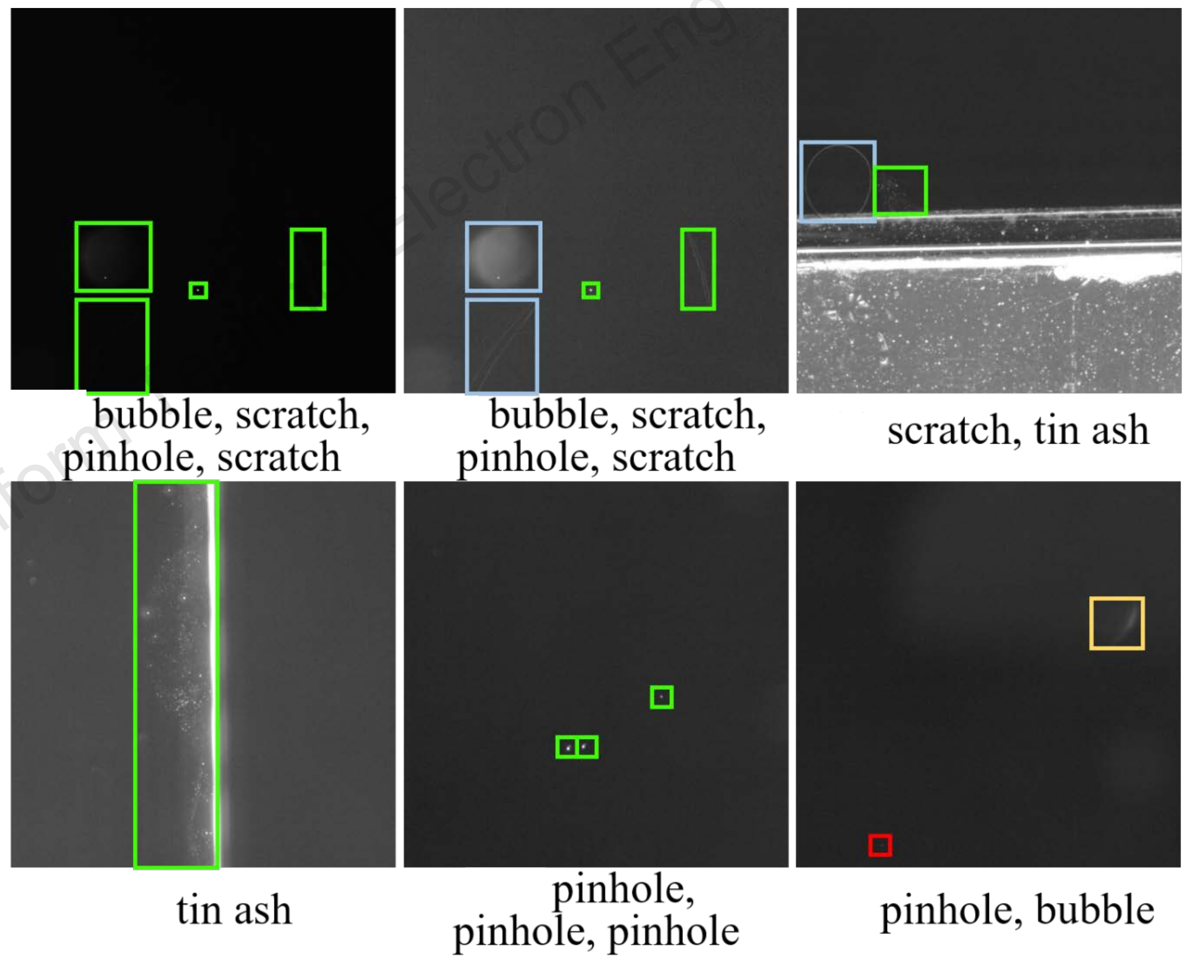
# Motivation

- 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

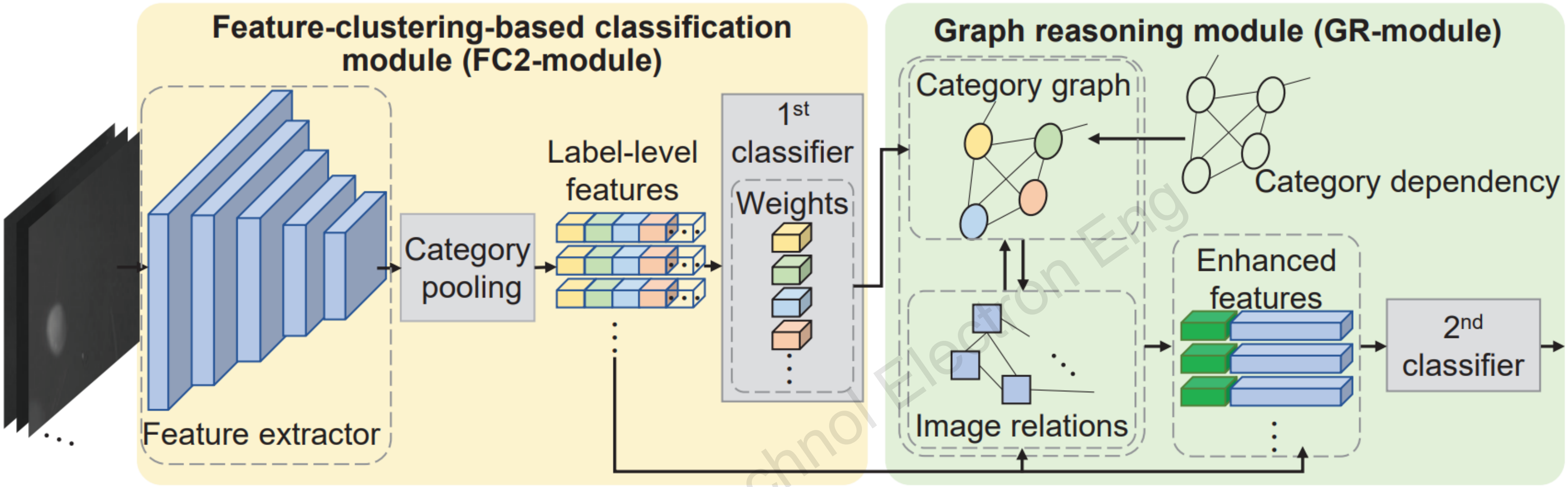



**Samples of mobile screen defects**

# 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.

# 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.

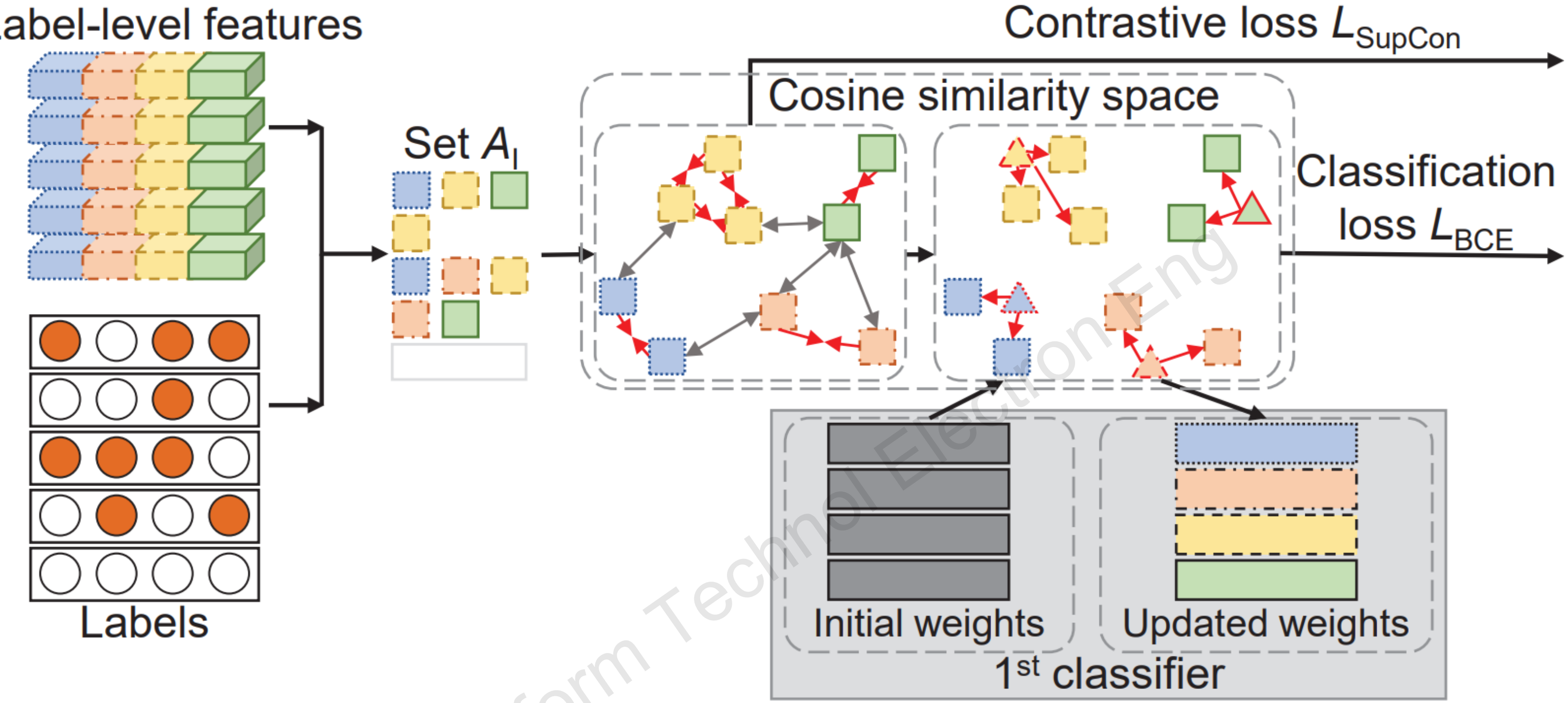
(2) Features and weights are fed into the graph reasoning module (GR-module) to enhance features.

(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.

# 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 |



- 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**

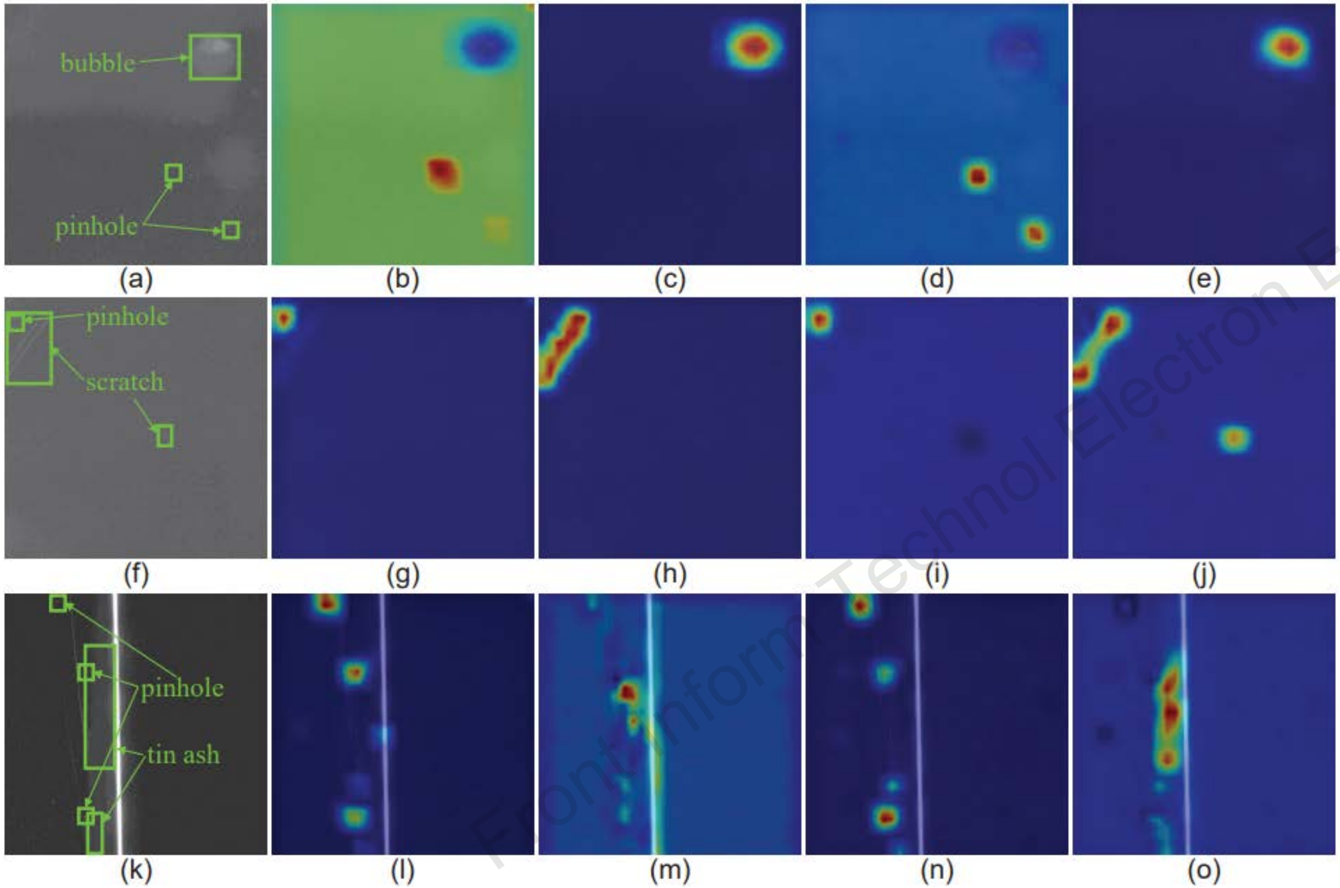
| Method | Accuracy | Precision | Recall | $F$-measure |
|---|---|---|---|---|
| ResNet-50 | 0.952 | 0.966 | 0.919 | 0.942 |
| VGG-16 | 0.967 | 0.963 | 0.827 | 0.890 |
| Inception-v3 | 0.971 | 0.963 | 0.953 | 0.958 |
| KSSNet | 0.953 | 0.828 | 0.713 | 0.767 |
| TDRG | 0.972 | 0.963 | 0.959 | 0.961 |
| 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



- 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.

# **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



- 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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