MATH 6380p Project 3: Smartphones Glass Defects Detection and Pixel-wise classification

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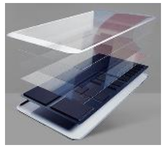
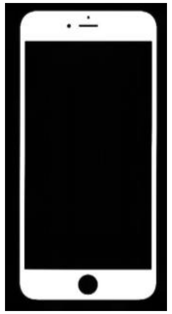
1. Introduction



Glass inspection of defects occurs at all stages of the production process which basically Performed mostly by human workers.
Conservative estimates place workers performing such inspection tasks at 20% of a factory's overall workforce. Based on the RAMLAB dataset [1], we proposed a robust method for the robust localization and classification of the defects using transfer learning and unsupervised learning. We get the good performance on the partially labelled mobile phone glass dataset.

2. Mobile phones Glass Datasets



We possessed 76 images of smartphones glasses with three kinds of defects: Scratch, light leakage and Dirt. Each image is combination of glass screen images and defect image, both are taken from a 16K line camera.

The Glass screen image is almost perfect but still have unlabeled defects. All defects artificially added to the glass images are labelled with their position and class. Real Glass screen is almost perfect with some scratches and unlabeled defects.

3. Method

Our Method follows, three different sections;

1. Localization of the defects.

Firstly the image is converted into binary image and then we estimated the bounding box for every white continuous region.

2. Distinguish between the real defects

We used non-maximum suppression to reduce the number of bounding boxes, and then passed thought a pre-trained ResNet – 18 to get the feature as shown in the Fig.1.

3. Training and Testing Process

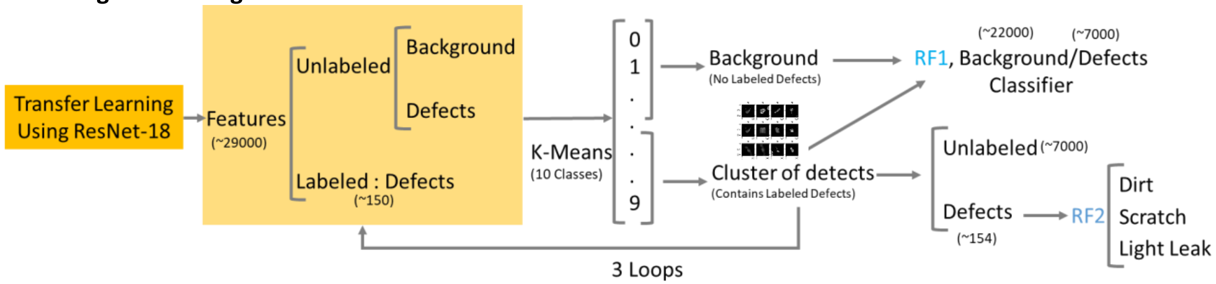


Fig2: Training Process. We use iterative k-means to augment the defect data class to train a model (RF1) which distinguish background and defects. Meanwhile, we use labeled defects to generate a defects classifier (RF2)

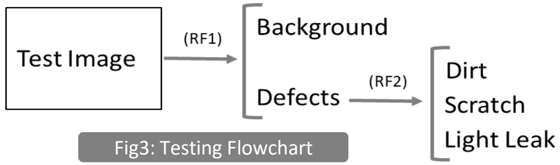


Fig3: Testing Flowchart

RF1 (Background / Defects	**AUC** = 0.94
RF2 (Defects)	Avg Recall = **0.81** Avg Precision = **0.82**

Table 1: Performance

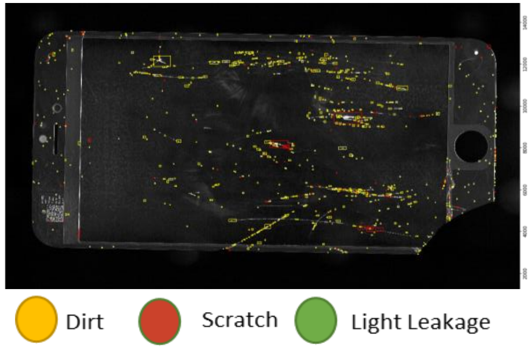


Fig4: Final Result

Project Source Code: https://github.com/UsmanMaqbool/MATH-6380p

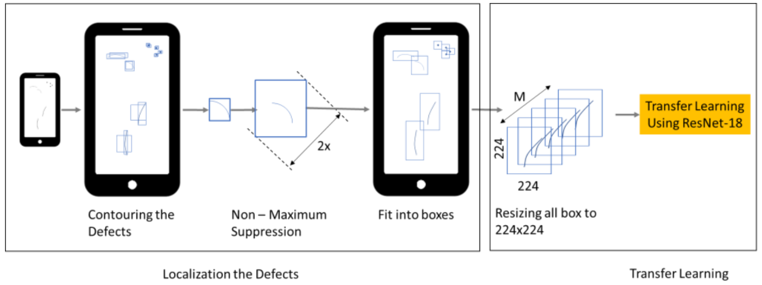


Fig 1: **Localization of the defects.**

5. Results

Figure 4 presents three types defects detected by our classifiers.
Table 1 shows the performance of two classifiers (RF1, RF2). AUC for RF1 is calculated by treating labeled defects as positive and others as negative. The average recall and precision for RF2 are averaged over three classes (dirt, scratch and light leakage), weighted by their support.

6. Conclusion

According to the experimental results, our proposed method performed excellent regardless of the enough dataset. The accuracy *performance* is also good. This scheme can used for the collection of the label's defects further, if we have large dataset, the Faster RCNN maybe used for for better performance.

7. References

[1] Glass Dataset by Robotics and Mult-Perception Lab HKUST.
[2] He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.