F-005

Glass Surface Defect Grading using Machine Learning Methods

Monikka Roslianna Busto‡ Pei Jiang‡ Hiroyuki Suzuki† Joong-Sun Lee‡ Takashi Obi‡

1. Introduction

Due to the increasing amount of digital devices being released every year, there is an inevitable increase in potential electronic wastes, most of which are actually still operable and recyclable with only defects present on its glass surface - making them resalable. As part of an environmental movement of recycling to minimize such wastes, modern gadget recommerce industry has ventured into reselling of secondhand electronic devices (such as smartphones, tablets, TV, etc.). In reselling, determination of price is crucial as it highly depends on the device's surface condition based on damage severity. Identifying the level of damage, also known as *grading*, of the electronic devices involves entirely human inspection. No automation of this inspection is being implemented yet. Depending on the severity of defects, a unit will then be classified into a severity level e.g. 0 (clean surface, with little to no damage). The aim of this study is to automate this visual inspection process for a faster turnout of recycling used smart devices utilizing glass surfaces.

In recent years, machine learning has paved way for many applications in manufacturing and product quality monitoring, especially for automating visual inspection. However, computer vision based frameworks specifically for grading glass surfaces are not fully explored. The main contributions of this work are as follows:

- An end-to-end computer vision pipeline for surface grading utilizing high-resolution specular diffusion images with corresponding labels pertaining to level of severity
- A combination of U-Net, Hu-Moments and k-Means is proposed to localize and classify defects in the glass surface images
- Grading is done by training a Random Forest classifier utilizing extracted features from aggregated defects

This paper is organized as follows: Section 2 presents a brief related work. We discuss our proposed framework in Section 3. Experimental results are presented in Section 4. We conclude the paper and provide recommendations for future work in Section 5.

2. Related Work

Machine learning based systems have been extensively used for detection and classification of defects in different kinds of objects and surfaces, of which the extracted information is used for performing grading to assess level of damage. In (Marino et.al., 2019), authors proposed a framework for localizing potato blemishes and using detected damage to classify based on severity of the blemishes [6]. In (Moallem et. al., 2017), a computer vision-based algorithm for apple grading is proposed using a combination of statistical, textural and geometric features as input to three classifiers of SVM, MLP and KNN [7]. In (Hou et. al., 2016), the authors used a patch-based CNN model with a supervised decision fusion model utilizing Expectation-Maximization (EM)-based method that identifies discriminative patches automatically for CNN training to perform rail surface damage severity grading [2]. These are few of the applications of grading in food and manufacturing industry. For glass surfaces, there is extensive work in classification or segmentation of defects but little implementation for performing overall severity assessment via grading. In (Li, et al., 2014), a PCA-based defect inspection system for mobile phone cover glass is proposed based on defect shapes and structures [4]. In (Lv,2019), a background reconstruction method based on autoencoders and a difference analysis method was proposed to detect defects on glass surfaces of mobiles phones [5].

3. Data and Proposed Framework

3.1 Data Description

The data used in this study are 60 high resolution images (4096x6500) acquired using a line-scan camera utilizing specular diffusion for highlighting textural differences caused by surface defects. The images are annotated by experts with grading 0, 1, 2 with increasing number indicating increasing level of overall damage severity. Each grading class contains 20 images.

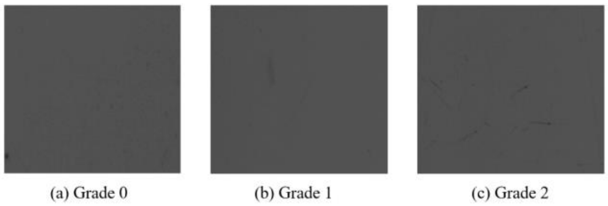

Figure 1 Example of Image Patches from Each Grading Level

3.2. Methodology

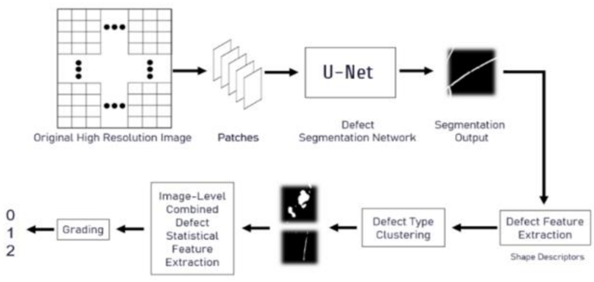

Figure 2 Diagram of Proposed Framework

Our framework aims to implement a system for performing in the following sequence. First, we detect all individual defects present in the surface via U-Net in patch-wise fashion. After segmentation, we cluster the individual defects to two clusters to quantify how many of each clusters of defects are present. Based on the high level-features obtained from the segmentation and defect clustering, we perform grading using these information as feature vectors for a trained classifier.

† Gunma University
‡ Tokyo Institute of Technology

3.2.1 U-Net for Defect Segmentation:

The U-net was trained as a means of segmenting individual defects per image of glass surface with the output as a binary mask. The original U-Net architecture [8] was modified to fit single-channel images with input shapes (256x256x1) set the same as the patches extracted from the high resolution images (see Figure 3). The number of feature maps in each of the contracting and expanding paths have also been reduced compared to the original architecture - allowing for less parameters to tune. The model takes in overlapping patches from the image as its input.

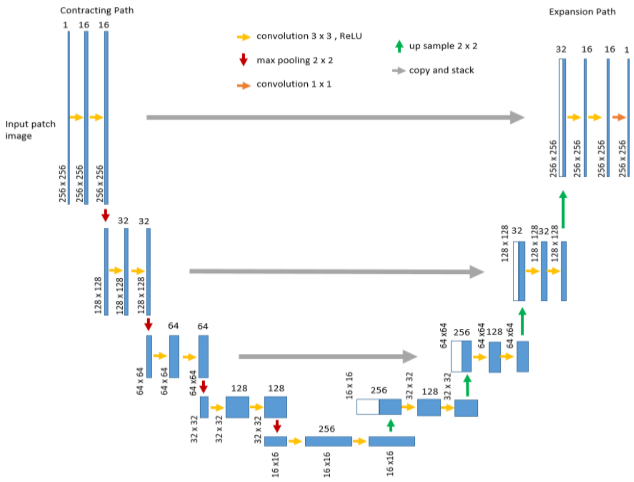

Figure 3 Modified U-Net Architecture

3.2.2. Hu-Moments and K-means for Defect Clustering:

After aggregating the segmentation output from the patches, we identify individual defects using contour analysis. We leverage the fact that the binary mask output contains shape information even without the original grayscale image and cluster defects using shape descriptors via Hu moments. Hu Moments are a set of 7 numbers obtained from central moments that are invariant to invariant to translation, scale, and rotation, and reflection [3]. These numbers are used as feature vectors for training Kmeans with parameter, $k = 2$.

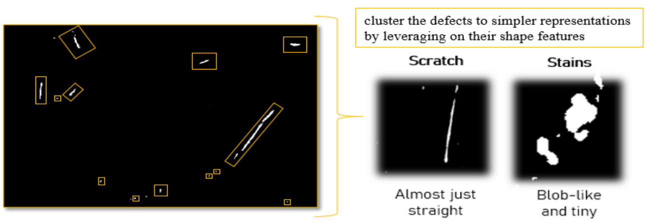

Figure 4 Defect Type Clustering via Hu Moments and Kmeans

3.2.3. Random Forest Classifier for Grading:

From the results of the segmentation and defect clustering, we collect high level features to be used as input vectors to a random forest classifier. These high level features are as follows:

(1) number of type 1 defect present (scratch-like),
(2) number of type 2 defect present (stain-like),
(3) total area covered by all defects (in pixels), and
(4) maximum length of a single defect (in pixels)

A random forest (RF) [1] is an ensemble method that uses a number of decision tree classifiers on randomly selected subset of training set and uses the mean prediction to avoid over-fitting. It aggregates the votes from different decision trees.

4. Experimental Results

The dataset was divided into training, validation and test sets at an 80-10-10 split. Cross validation using 15 folds and grid search for random forest classifier was applied to the training set. The average of the results of cross validation are shown in Table 1.

Table 1 Average scores for 15-fold cross validation

	Precision	Recall	F-Score
0	0.958	1.0	0.972
1	0.764	0.875	0.7889
2	0.625	0.667	0.639

To estimate the performance of the trained model, the model is run on unseen test set. The confusion matrix for each grading level is shown in Table 2.

Table 2 Confusion matrix for test set

Grade	0	1	2
0	1	0	0
1	0	1	0
2	0	0.167	0.833

5. Conclusion and Future Work

In this study, we proposed a framework for grading - determining overall severity of damaged glass surfaces. We aggregate information from detected defects and train a supervised machine learning classifier to assess severity. Experimental results demonstrate feasibility of defect grading using a combination of machine learning methods. For future work, we aim to increase the dataset and use more features to improve the performance.

References

[1] Breiman, L. Random Forests. Machine Learning 45, 5–32 (2001). https://doi.org/10.1023/A:1010933404324
[2] Hou, L., Samaras, D., Kurc, T. M., Gao, Y., Davis, J. E., & Saltz, J. H. (2016). Patch-Based Convolutional Neural Network for Whole Slide Tissue Image Classification. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). doi: 10.1109/cvpr.2016.266
[3] Hu, M.-K. (1962). Visual pattern recognition by moment invariants. IEEE Transactions on Information Theory, 8(2), 179–187. doi: 10.1109/tit.1962.1057692
[4] Li, Di, et al. “Defect Inspection and Extraction of the Mobile Phone Cover Glass Based on the Principal Components Analysis.” The International Journal of Advanced Manufacturing Technology, vol. 73, no. 9-12, 2014, pp. 1605–1614., doi:10.1007/s00170-014-5871-y.
[5] Lv, Chengkan, et al. “A Fast Surface Defect Detection Method Based on Background Reconstruction.” International Journal of Precision Engineering and Manufacturing, vol. 21, no. 3, Sept. 2019, pp. 363–375., doi:10.1007/s12541-019-00262-2.
[6] Marino, S., Beauseroy, P., & Smolarz, A. (2019). Deep Learning-based Method for Classifying and Localizing Potato Blemishes. Proceedings of the 8th International Conference on Pattern Recognition Applications and Methods. doi: 10.5220/0007350101070117
[7] Moallem, P., Serajoddin, A., & Pourghassem, H. (2017). Computer vision-based apple grading for golden delicious apples based on surface features. Information Processing in Agriculture, 4(1), 33–40. doi: 10.1016/j.inpa.2016.10.003
[8] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. Lecture Notes in Computer Science Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015, 234–241. doi: 10.1007/978-3-319-24574-4_28