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Smart-Inspect: Micro Scale Localization and Classification of Smart Phone Glass Defects for Industrial Automation

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Abstract— **With the rise in smart device manufacturing, the presence of any type of defect on the glass screen has a great impact on the quality of smart devices. This paper presents a robust approach for intelligent micro-scaled localization and classification of defects using semi-supervised learning on 16K pixel image of mobile phone glasses. Our approach features an efficient recognition and labeling of three types of defects: scratches, light leakage, and pits. Our method also differentiates between the defects and light reflections due to dirt particles and sensors regions, classified as background. We use a partially labeled dataset to achieve high robustness and excellent classification of defects and background as compared to PCA, multi-resolution and information fusion based algorithms. In addition, we incorporated two classifiers at different stages of our inspection framework for labeling and refining the unlabeled defects. We successfully enhanced the inspection depth-limit up to 5 microns. The experimental results show that our method outperformed human inspection in testing the quality of glass screen samples by identifying defects in samples that have been marked as good by human inspection.**

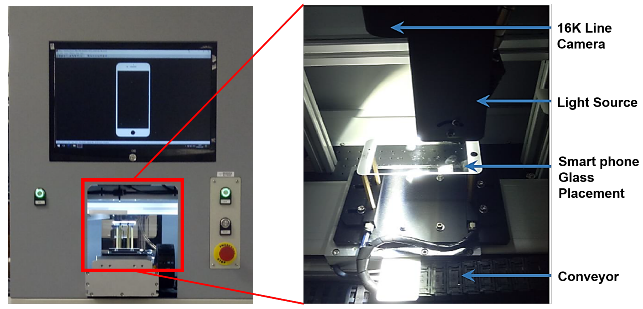

Fig. 1: Smart Phone Glass Inspection System. The left image shows the front view, and the right image shows the inside view of the experimental system.

I. Introduction

In the era of robotics and automation, AI is helping to solve many difficult problems, where humans are unable to reach that level. Glass inspection is one of the key challenging problem for the glass manufacturing industry. Due to industrial competition, manufacturing companies are facing financial loses due to inspection time and the limitation of the workforce. Furthermore, the presence of defects that human eyes are not able to see, has great importance in the quality of smart device glass. Nowadays, companies are showing great interest in investing in automation systems along with state-of-the-art techniques, that can help them overcome these problems; hence boosting the production line and in return sales profits.

A variety of inspection systems have been proposed to solve the inspection problems for different market niches of limited types of glass. For defect inspection of satin glass and float glass, researchers have used machine learning techniques [1, 2, 3, 4]. Several frameworks based on image-processing have been proposed for satin glass [4] and glass bottles [5]. Furthermore, some optical-based approaches have been proposed to detect micro-cracks in glass [6], detect surface defects in touch panel glass [7], and inspect window glass [8]. Some contributions have been made related to rough set theory to defect detection of automotive glass for vehicles [9].

A huge rise in the production of smart device glass has been noticed in the last ten years. Many technology companies who manufacture smart gadgets such as mobile phones, tablets, laptops, and smartwatches are producing millions of sets each year. In smart device glass, not only is large workforce required but also time is another important key constraint in inspecting the smart device glass. Due to the limitation of accuracy, human eyes are only able to detect a defect over 0.1 millimeters. Also, the average time for inspecting one smartphone glass is about 1-2 minutes.Therefore, meeting the market demand and increasing the production rate is becoming challenging without incorporating robotics, automation and AI in the production lines to solve inspection problems.

For smartphone glass inspection, the high-level accuracy and speed are the key-challenging tasks. Currently, the state-of-the-art works [10] present a mechanism based on principal components analysis (PCA) for defect inspection of mobile phone cover glass. This is limited to detecting the scratch defects only. Using these techniques, it is complicated to classify the light leakage and specks of dirt on the smartphone's glass.

Our proposed scheme *SmartInspect* uses an experimental setup for smartphone glass inspection which will be discussed in detail in section IV. Based on the dataset

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collected using the inspection system, our target is to precisely localize the defects over full screen glass image and classify them to different types of defects such as scratches, pits and light leakage, along with backgrounds such as sensors areas, light reflections and dirt. The very large-sized image can have many different combinations of defects and background. SmartInspect makes possible the identification of defects, backgrounds, and sensors regions. Moreover, it also works in the characterization of the type of defects.

We begin by outlining related work (Sec II) and our problem description in Sec III. Sec IV presents our proposed method and framework for smart inspection of mobile phone screen glass. Sec V demonstrates the experiments and results obtained by smart-inspect including both quantitative and qualitative evaluations.

II. Related Work

This section presents a review of recent work related to the glass inspection techniques and frameworks. In literature, minimal contributions to this area have been found specifically related to smart device glass inspection techniques, although some methods are present that are related to detecting several glass defects of LCD and general glass. [11] introduced a fan-beam laser-light-based method for inspecting the scratches and dust over the LCD panels. Recognition of bubbles of the glasses has been done [12]. In this method, the authors proposed a technique called binary feature histogram (BFH), which helps in the characterization and classification of glass defects. In this work they used the AdaBoost algorithm.

An online distributed float glass inspection scheme is introduced in [2], which uses the OTSU method along with image filtration using gradient direction. They also used the adaptive surface for estimating the downward threshold. This system can quickly detect the bubbles, light reflection and lards. [13] shows a two-phase method for an LED glass defect inspection framework using machine learning, which involves both training and testing process. Research work based on wavelet analysis and fuzzy k-nearest neighbor is presented in [14] for inspection of general glass. This approach can help in identifying defects such as bubbles, inclusions, distortion, tin drop and cracks.

Furthermore, Di Li [10] proposed a method for surface defects inspection of smartphone cover glass. The authors applied a PCA algorithm to work on smartphone cover glass, whereas all the previous works have concentrated on LCD or general glass. This principal-components-analysis based method can help in identifying typical defects such as scratches, cracks, edges, angle cutting, and deformation. The manufacturing process of mobile phone glass is very much different than for general glass, and the quality needs further improvement in diagnosing the defects, if any. Their proposed system not only detects the defects but also able to recognize them to some extent. After taking inspiration from PCA in facial recognition, [10] used it in their framework to classify the defects. Meanwhile, each image is taken as a defect face and sets up a training set for defects features estimation and classification using PCA.

There are some semi-supervised methods such as Pseudo-Label [15], learning using deep generative models [16] and with ladder networks [17], and learning by association [18], but these approaches require labeled dataset for robustness evaluation.

A smartphone glass sample has many defects along with sensors regions which includes holes for the camera, speaker, and buttons. The methods discussed above are not able to process a full glass image because they are unable to distinguish between the background region and the original defects. Furthermore, labeling of 16K glass images dataset for up to 5 microns defects is also another challenging aspect which cannot be handled by previously discussed approaches.

III. Problem Description

Defects inspection and classification is the fundamental challenging problem. The methods discussed in II shows good results if the target is only to detect them. However, their outcomes may have wrong labeling. For instance, in the case of dirt particles, these techniques are unable to distinguish them from scratches and dirt. Although dirt is not a defect. A more critical challenging problem is the identification of the background sample because the glass samples might have written text and QR Codes. Another difficult task is to detect defects that are very small in dimensions.

As will be illustrated by our experiments, *SmartInspect* can help in the estimation of small-sized defects, which a human eye is unable to capture. Furthermore, our algorithm outperforms state-of-the-art in differentiating the background from the defects. Our contributions are as follows;

- *SmartInspect* can work on raw images (without any enhancement) and full smartphone glass images (without cropping). This makes it much more powerful and efficient than the current state-of-the-art techniques [10, 14], which can perform only after taking the transparent glass regions by cropping the sides of glass.
- Our method outperforms in precise localization and accurate classification of tiny defects (5 microns meter) that human eyes cannot see.
- We proposed a robust method where the system can perform excellently based on the partially labeled small dataset.
- *SmartInspect* can label large datasets of smart phone glasses with high accuracy.

IV. Formulation and Methodology

A. Proposed Approach

SmartInspect is generated by four-stage processing. In stage I, all suspicious white continuous regions on each image are cropped along their bounding boxes, which are detected by the contours finding algorithm 1. In stage II, a pre-trained convolutional neural network (CNN) is used to extract the features of those crops. In stage III, based on the characteristic of our dataset, we only have few labeled defects and sensors regions. Background and defects classifier (BD) is a binary classifier that divides defects into two classes: defects and background. It also controls the feedback iterations from defects to the K-means clusters. We use K-means several times and drop those clusters excluding or containing a relatively low proportion of labeled defects in each loop until the number of dropped crops is less than the preset threshold. This stage cuts the redundant background crops and greatly reduces the number of defects. In the final stage IV, a Random Forest based five-class defects classifier (DC), is trained by the labeled defects. The four-stage processing works on three sections;

1) Dataset: Our dataset consists of 274 glass images. All of the 16K pixel images have different combinations of defects and background regions.

2) Localization of the defects: Firstly a Sobel filtered with kernel size of 3 is applied to the grey image of glass. Then this image is converted into a binary image and dilation is applied on the binary image to enhance the connectivity of regions. After that, we estimate the bounding box along with its size and original position for each continuous white region by non-maximum suppression. Intersection over Union (IoU) is estimated between each bounding box with the other bounding boxes. Moreover, based on the non-maximum suppression threshold (T_{nms}), these boxes are merged into one. The scheme is further explained in algorithm 1. All of the continuous white regions are padded by zeros to achieve square regions resulting to a single class object. In the end, all the square boxes that correspond to a single class object are resized to 224×224 pixel batches. For the whole dataset, we obtained $M = 226,222$ crops, as shown in Fig 2.

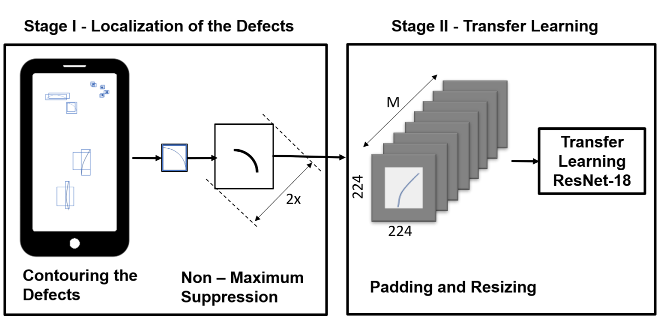

Fig. 2: Feature Extraction for Transfer Learning

Algorithm 1: Continuous Regions Selection Algorithm

Data: Glass Image I of size $[16384 \times 24576]$ captured from the 16K line camera.
T_{nms} is the non maximum suppresion threshold
Result: $R = \{r_1, ..., r_M\}$ continuous regions boxes of size $[224 \times 224]$
initialization;
$I_s = Sobel_{filteration}(I_b)$ using kernal $(5,5)$;
$I_b = Threshold_{binary}(I_s)$ at value of 200;
$I_{dilated} = Dilation(I_b)$ using kernal $(3,3)$;
Find contours $C = \{c_1, ..., c_N\}$ of all the white regions (pixels) $S_d = \{s_1, ..., s_N\}$;
$R \leftarrow \{\}$;
$T_{nms} = 0.2$;
while $C \neq empty$ **do**
  $i \leftarrow argmax\ S_d$;
  $O \leftarrow c_i$;
  $R \leftarrow R \bigcup O$;
  $C \leftarrow C - O$;
  $S_d \leftarrow S_d - s_i$;
  for c_j *in* C **do**
    if $iou(O,\ c_j) \geq T_{nms}$ **then**
      $C \leftarrow C - c_j$;
      $S_d \leftarrow S_d - s_j$;
while $R \neq empty$ **do**
  $[w, h] = size(R_i)$;
  if $w < h$ **then**
    $R_i \leftarrow padding^{x=h}_{zeros}(R_i)$;
  else if $w > h$ **then**
    $R_i \leftarrow padding^{y=w}_{zeros}(R_i)$;
  $R_i(224, 224) \leftarrow R_i$;
return R

3) Distinguish between the real defects: These include background, sensors areas, scratches, dirt, pit, crack, fingerprint, QR, and light leakages regions. As our approach is semi-supervised, we labeled 1070 crops samples manually. Background, scratch, pit cracks, dirt, sensors, and light leakage consist of 30, 270, 210, 280, 150 and 130 regions respectively. Transfer learning is used to process all crops for the classification. The pre-trained neural network ResNet18 [19] is used as a feature extractor. Each crop is converted to a 512-dim feature vector after passing through ResNet18.

B. K-means Clustering

In order to distinguish real defects and the background, we used Random Forest to train BD classifier. Due to the limited number of labeled data, we can not train a background-defects classifier directly by using the supervised approach. Therefore, we design a semi-supervised method to train this classifier. We use k-means iteratively, for assigning data to non-overlapping subgroups (clusters), a type

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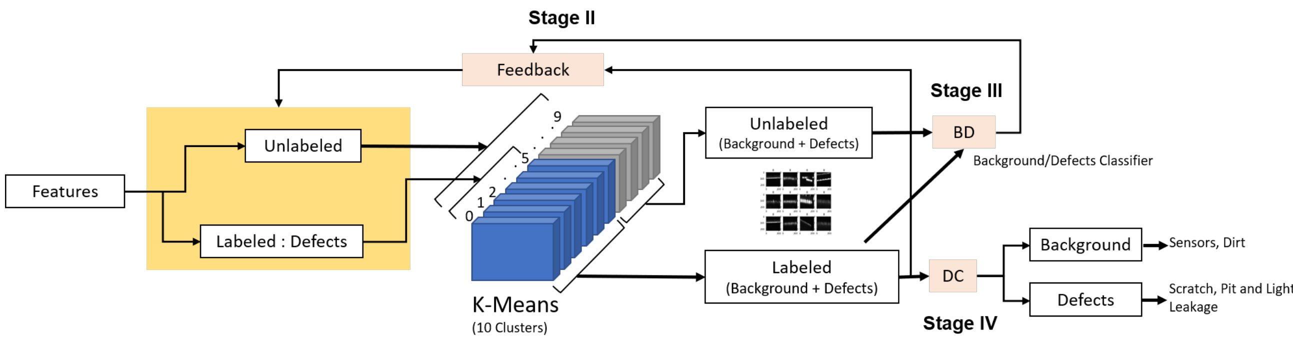

Fig. 3: Semi-supervised Learning for Defects and Background Classifications

of unsupervised learning followed by approach known as Expectation-Maximization. Next, based on the refined labels, we filter some clusters until this algorithm converges. The loss function used for k-means clustering is as follows:

$$J = \sum_{i=1}^{m} \sum_{k=1}^{K} w_{ik} \left\| x^i - \mu k \right\|^2$$

For each k-means iteration, all data points (the feature vector of each crop) are divided into 10 clusters (K=10). Then based on the labelled data, we retain the top six clusters containing the highest proportion of labeled data and cast them into the next iteration. Specifically, by using the feedback, as shown in Fig 3. The iteration continues until the number of dropped data is less than our preset threshold. After dropping all background data, we retain real defects. We train an intra-class classifier DC to classify the real defects into three different defects: scratches, pits cracks and light leakages along with two background objects: dirt and sensors regions.

C. Inspection System Hardware

The experimental setup used in introducing the proposed framework is shown in Fig. 1. A 16K line camera has been used to scan the glass image. The human eye can detect only a defect over 0.1 millimeters. To decrease this limit, we have used a 16K line camera, which makes our system capture the defects down to 5 microns.

First, the smartphone glass is placed under the camera and a lightening system, at a certain height, as shown in Fig. 1. Then the image is captured. While capturing the image, the line camera moves from top to the bottom of glass to get a full scan glass image. The captured image is shown on the screen. A core i9 processor is used in the system for handling 16K resolution image. The size of each image is about 400 MB, which is very large as compared to simple camera images. To process a huge sized image, the SmartInspect framework is proposed to localize the defects precisely, and efficiently classify them separately using the machine learning technique.

V. Experiments and Results

For the robustness evaluation of the SmartInspect scheme, we test on glass images with many different defects, as well as on some positive glass samples.

A. Quantitative Evaluation

Table I shows the quantitative evaluation of our semi-supervised method for the glass inspection scheme. Where TP, FN, TN, and FP corresponds to true positive, false negative, true negative, and false positive, respectively. All the test images have defects on it, such as scratches (S-type), pits (P-type) and light leakage (LL-type) along with non-defect regions of dirt (D-type) and sensors regions (SR-type). Our system is not placed in a dirt-free environment, and due to glass edges, light leakage is a compulsory component on all the samples. Our system outperformed on clean, scratch, and pit sample. For the samples with dirt, the overall accuracy significantly decreased to 75% due to the wrong prediction of dirt regions as pits, scratches or light leakages.

B. Qualitative Evaluation

Fig. 4 shows the performance by inspecting the glass image full of defected areas. We separated the defects using the bounding boxes. Regions marked in red are scratches, green represents light leakage, yellow shows dirt particles. Sensors regions and light leakages are marked in purple and cyan respectively. For our dataset, we choose the Random Forest method, which performaned better than SVM to generate the five classes classifier by training 1072 labeled pieces of data.

The interesting fact to note is that SmartInspect scanned the whole image and intelligently identified the background regions. Frameworks [10, 14] treated all the white regions as defects. However, SmartInspect did not mark the background regions as defects. Fig. 4 clearly shows the background regions such as QR code, speaker, button, sensors, and camera. Some light reflections and dust particles are observed in these areas, which have been displayed in cyan and yellow boxes respectively in Fig 4.

Furthermore, we tested our algorithm on glass samples which have been previously marked as positive by human inspection. Fig 5 shows one of the glass inspection results

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TABLE I: Accuracy Evaluation of the Proposed Method

Evaluation Glasses	Defected Regions	Type	TP	FN	TN	FP	Sensitivity	Specificity	Precision	Overall Accuracy
Clean Sample	133	D, LL, SR	128	3	1	0	0.9770	**1**	**1**	**0.9777**
Scratch Sample	191	S, D, LL, SR	181	0	9	1	1	0.9	**0.9945**	**0.9947**
Dirt Sample	235	D, LL, SR	177	0	0	58	1	0	0.7531	0.7531
Pit Sample	134	P, D, LL, SR	126	0	1	7	1	0.125	**0.9473**	**0.9477**

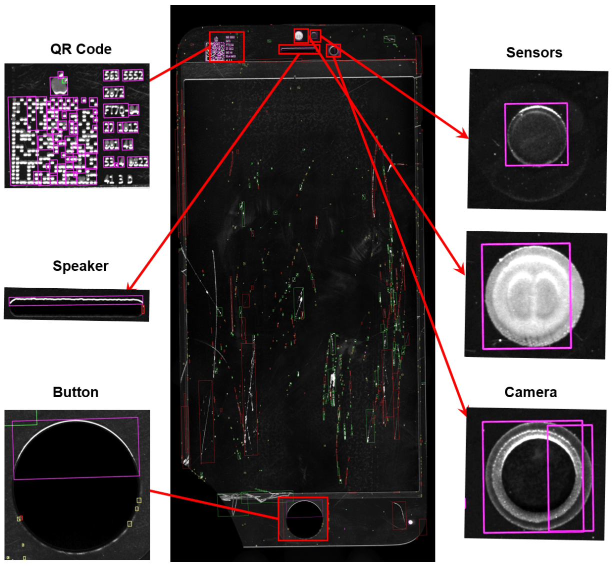

Fig. 4: SmartInspect test performance on key-challenging test images with hundreds of defects. Sensors areas such as QR Code, Camera, Speaker button have been successfully distinguished from the defects.

of positive samples. We can notice that SmartInspect outperformed human inspection in evaluating the quality of glass samples. Three defects have been localized and classified. For instance, two light leakages (D-1 and D-3) and one dust particle (D-2) are detected which are shown in orange and green boxes respectively in Fig 5.

Table II shows the comparison of SmartInspect with the current advanced methods. It shows that our system is quite intelligent in recognition of background areas. It is also robust to achieve a high level of accuracy of up to 5 microns of the defected area, which is very important in smart device glass. If the glass has defects of light leakage or dirt, this can reduce the image quality of the screen.

VI. Discussion

Using SmartInspect, we can label many 16K mobile glass images, which are otherwise considered challenging to correctly label at micro scale. SmartInspect can help in the generation of the ground truth images much faster than doing so manually, as it helps in the precise cropping and classification. Once all the classes are refined, it becomes easy to generate thousands of images with labeled defects. Another method is by putting defect patches on the smartphone glass and save the labels for ground truth.

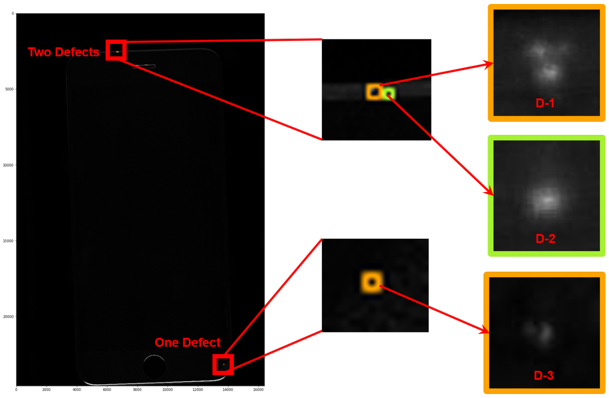

Fig. 5: SmartInspect performance on the positive samples. Green box shows the light leakage whereas the orange box shows dirt detected on the glass screen.

A. Ablation Study

Using the proposed scheme, a whole glass image can be taken as input without cropping and processing the transparent areas. Without enhancing the images defects by applying some filtration tools and increasing the sharpness of captured images, our proposed technique outperformed the state-of-the-art on all the samples. The result is shown on right and left side of Fig. 4 for better visualization.

However, capturing system requires further improvements, such as a controlled testing environment. By using the 16K camera, we are able to detect defects down to 5 microns. Although it detects dust, so the glass samples must be taken in the dust-free area otherwise it will affect the results as explained in section V-A. Sometimes specks of dirt seem to be scratch as in the clean image. Also, a pit happens along with scratch. Thus, the overall sample is treated as pit defected. Furthermore, the sample must be put in an experimental setup by using gloves to avoid fingerprints on the screen.

B. Minimization of Inspection Time

To reduce the inspection time is another key-challenging problem. There are several methods to localize the objects in real-time. Faster R-CNN [20] is one of the best framework. However, it requires a vast labeled dataset. SmartInspect now makes it possible to label objects over smart phone glasses to be used with Faster R-CNN for real time defect detection. Processing each sample currently takes about 10-20 sec, which is quite long for industrial application.

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TABLE II: Robustness Comparison of the Proposed Method

Inspection Feature	PCA based method [10]	MIF Based method [14]	Proposed Method (*SmartInspect*)
Detection of Defects	YES	YES	YES
Classification of Defects	NO	YES	YES
Distinguishing Defects and Background	NO	NO	YES

Another idea is to use online network systems, where many computers are connected with the server [14]. This can help in enhancing the throughput of the overall system and will be further enhanced using GPU integration along with deep learning techniques.

VII. Conclusion

According to the experimental results, our semi-supervised method performed excellent with high accuracy at micro scale. It is capable of processing the smart phone glass image as a whole without cropping transparent region from it. Our approach has the ability to meet the high demand of quality-inspection in production lines of several smart devices in order to compete the market. Furthermore, the current localization time of the defects can be reduced by labeling vast smart phone glass images using Smart-Inspect.

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