The Visual Inspection of Solder Balls in Semiconductor Encapsulation

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Abstract: The growing demand for increasing memory storage capacity has required a high density of integration within the semiconductor encapsulation and, consequently, has made this process more complex and susceptible to failures during the production stage. In the semiconductor encapsulation area, the costs of materials and equipment are high and the profit margin is narrow, making it necessary to rigorously inspect the process steps to keep the productive activity viable. This work addresses the problem of quality control in silicon wafers soldering procedure, allowing error detection before the epoxy resin molding process, generating useful information for correcting equipment configurations and predicting failures from the raw materials and inputs used in the process. We propose an approach to classify solder balls, in the soldering process of silicon wafers on Ball Grid Array (BGA), contained in the Printed Circuit Board (PCB) substrates. The proposed methodology is composed of two main steps: *i*) Solder ball segmentation; and *ii*) Solder ball classification through deep learning. The proposed predictive model learns the relation between visual features and the different soldering conditions. Real and simulated experiments were carried out to validate the proposed approach. Results show the obtained accuracy of 99.4%, using Convolutional Neural Network (CNN) classification model. Furthermore, the proposed approach presents high accuracy even regarding noisy images, resulting in accuracy of 92.8% and 75.7% for a Salt and Pepper and Gaussian noise, respectively, in the worst scenario. Experiments demonstrate reliability and robustness, optimizing the manufacturing.

1 INTRODUCTION

Automated inspection of semiconductors has been the focus of numerous research efforts in Microelectronics and Industrial communities in the past few years (Zhang et al., 2022). The semiconductors inspection has the role of feeding back the methods with information on specific errors, which can be correlated with production problems. The semiconductors analysis includes the assessment on occurrence of failures due to the materials involved in the process or inadequate definitions of the machine parameters (Zhang et al., 2021).

In the semiconductors context, the production of memory devices represents a great manufacturing challenge, especially due to the small component's dimensions and the required precision in its operation. Additionally, the market demand for memory devices has increased massively, requiring the expansion of memory production volume, making the manual in-

spection process critical (Chang et al., 2018).

The use of the conventional visual inspection process, regarding a trained human operator, presents effectiveness between 80% and 90% of cases. However, after the first half working hour, the human operator visual acuity decreases significantly, for the analysis of a single type of defect [1]. In Figure 1, is presented an example of a human visual inspection of silicon wafers, where the human operator should visually run through all the components on the PCB substrate looking for different types of defects.

In this paper, we present an approach to classify solder balls, in the soldering process of a silicon wafer, called *die*, on BGAs, contained in the PCB substrates. The solder ball is classified into three categories: *i*) correct; *ii*) absence; or *iii*) failure. We also introduce a CNN architecture for supervised classification of solder balls, which learns the main features that represent all approached types of soldering conditions. Experiments in real-world scenarios and simu-
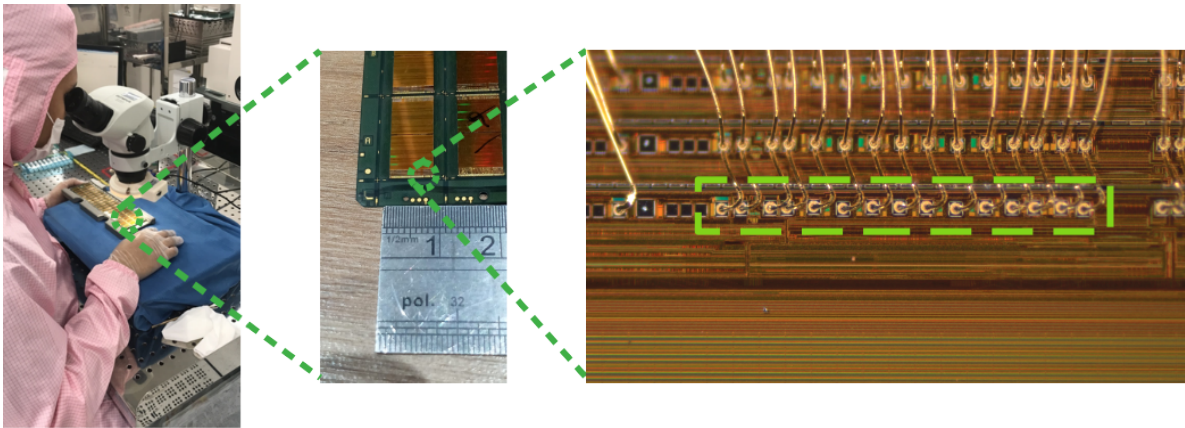
Figure 1: Conventional visual inspection of memory devices, in soldering process of silicon wafers. Additionally, are contrasted the sizes of a die and solder balls.

lations show that the obtained results are accurate and applicable in industrial scenarios.

Our main contribution is to provide an approach, based on deep learning, to detect failures in the die soldering process. Furthermore, the proposed strategy provides a robust solution for a challenging component, in micrometers scale. Also in Figure 1, it is possible observe the challenging size of solder balls and the involved features to depict the problem.

The remainder of this paper is structured as follows. In Section II we present a discussion on related works regarding Semiconductor Inspection. The proposed methodology is presented in Section III and validated by real and simulated experiments discussed in Section IV. Finally, in Section V we draw the conclusions and discuss paths for future investigation.

2 RELATED WORKS

Problems related to automatic visual inspection are of significant importance and have been the subject of intensive investigation (Huang et al., 2014) (Vafeiadis et al., 2018)(Zhang et al., 2022). For fault detection, the majority of works perform classification of presence or absence of faults, in manufacturing processes (Rocha et al., 2016) (Zhang et al., 2021).

Many industrial applications are addressed as a fault detection approach. In (Rocha et al., 2016), a visual inspection approach is presented to detect absence/presence of surface mount components (SMC) on printed circuit boards (PCB). The authors propose a methodology based on the combination of Machine Vision and Machine Learning (using Support Vector Machine (SVM)) to detect component absence, with more quality and precision, using noisy digital images acquired directly from PCB industrial production line.

The obtained results demonstrated the robustness of the methodology, obtaining 97.25% of accuracy.

(Zhou et al., 2017) has proposed a detection approach for oil-air and oil-water interfaces, from images of transparent tubes containing water and oil. A statistical based approach to detect the mentioned interfaces is used. Through real experiments, results show that the multi-interface detection method has high precision and reaches the requirements of industrial applications.

In some industrial applications, semiconductor inspection is a paramount task. (Srivastava et al., 2016) presents an inspection approach for patterned wafer during the chip fabrication. The authors proposed an unique combination of Broad-Band light with Dark Field Apertures, to reduce potential defects in manufacturing process. From the experiments, the proposed inspection approach demonstrates effectiveness in real application, achieving approximately 15 wafers per hour.

The authors of (Cao, 2021) proposed a robot vision inspection system. The industrial robot is used to detect the surface defects of semiconductor metal targets online. In this paper, the main goal is to complete a high purity semiconductor metal target processing inspection task. As result, the system can completely replace the traditional manual testing, and improve the machining quality and efficiency of semiconductor metal target.

In (Zhou et al., 2021) is presented an approach to inspect the chips in the wafer backside, during the manufacturing process. In semiconductor analysis the scan result is evaluated and compared to the Backside Database (BDB), to quantify the accuracy achieved. The experiments demonstrate the effectiveness of the proposed approach for backside defect Monitoring strategy.
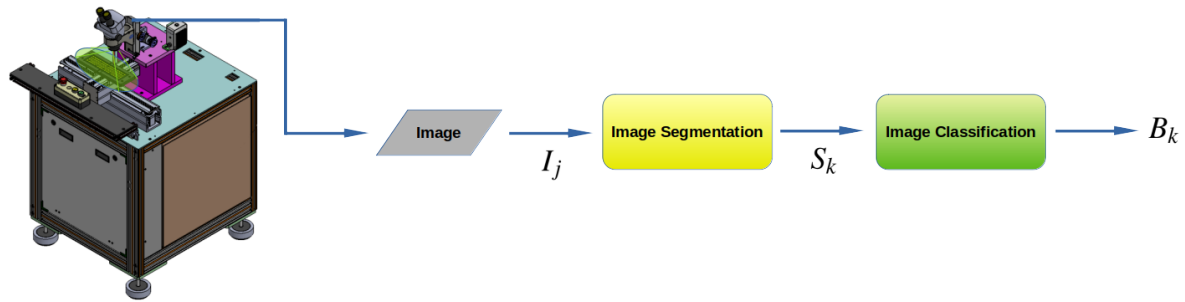
Figure 2: Overview of the proposed approach for automatic visual inspection for silicon wafer soldering process, through the stages: *i*) Image Segmentation; and *ii*) Image Classification through deep learning.

Still in semiconductor inspection context, but regarding the soldering process, (Zhang et al., 2021) proposed a strategy to inspect internal circuit boards in the production of water pumps. In this paper the authors design a solder joint inspection system based on machine vision, which can detect the status of solder joints and feed back the current soldering results to the workers. The method solves the problem of automatically detecting the welding quality of the circuit board in the manual welding process, greatly improves the production efficiency of the workshop production line, and shortens the product manufacturing cycle.

(Chang et al., 2018) has proposed an inspection technique for automated optical inspection (AOI) and solder paste inspection (SPI), in SMT line. The authors used a machine learning based approach called automatic mistake reduction (AMR) for Classification of solder joints in production line. The experimental results showed that the proposed method is not only more efficient, but also provides an accurate recognition rate in the SMT process.

In (Zhang et al., 2022) is proposed an approach for solder joint defect detection on industrial manufacturing process. For this, the authors used a deep learning based technique to learn features and detect the failures through a CNN model. Through the experiments the effectiveness of the proposed models is verified by real-world 3D X-ray images.

The majority of the existing solutions for solder evaluation are based on the classification of the solder conditions on positive or negative cases (Chang et al., 2018). The closest approach, regarding the methodological strategy, using CNN models, inspect solder joints from x-ray images (Zhang et al., 2022). Additionally, the soldering process assessed by the majority of works tackle milimiters and centimeters scales.

The presented approach is particularly interesting because it proposes an automatic solder ball classification for PCB production. Additionally, it is important to mention that unlike other works whose tackle solder conditions in millimeters and centime-

ters scale, our work tackle solder balls in micrometers scale, representing a great challenge for an accurate automatic visual inspection in semiconductor encapsulation process.

3 METHODOLOGY

In this paper, we propose an automatic visual inspection for silicon wafer soldering process, based on visual features and deep learning combining. The proposed approach tackles the solder ball classification problem, during the silicon wafer soldering process, detecting failures in the semiconductor encapsulation stage. An overview of the proposed methodology is shown in Figure 2, whose details will be presented in the next subsections.

In Figure 2, we present an overview of the proposed approach, highlighting the main steps to achieve the solder ball classification, indicating the correct, absent or failure condition in the ball soldering stage. To reach this goal, images are acquired continuously and an image segmentation stage is performed. Different features are learnt in a deep learning procedure, understanding the solder conditions for an efficient classification.

Our problem can be summarized as follows:

Problem 1 (Automatic Visual Inspection). *Let $I = \{i_1, i_2, \ldots, i_n\}$ be a series of silicon wafer images provided by a camera. For every $i_j \in I$, is extracted a set of segmented solder ball images $S_j = \{s_1, s_2, \ldots, s_m\}$. Also let $\mathcal{B} = \{b_1, b_2, \ldots, b_k\}$ be a series of previously known solder ball labels. Our main goal is to correctly associate an unknown segmented solder ball image (s_w) to the correspondent solder ball label (b_l), representing the solder ball condition during the soldering process.*

3.1 Image Segmentation

In this work the images (*I*) are initially acquired in Red, Green and Blue (RGB) model. The first step to inspect the soldering stage, during the semiconductor encapsulation process, is to segment the solder balls (*S*) contained in the silicon wafer images.

For this solder ball segmentation step, the Haar cascade method, using boosted cascade of simple features, is used (Viola and Jones, 2001). The Haar cascade method works like a machine learning approach, where the cascade function is trained from a set of images representing positive and negative cases.

In Haar cascade, for solder ball detection, rectangle features are used to learn patterns. For this, the sum of the pixels which lie within the white rectangles are subtracted from the sum of pixels in the grey rectangles. Some rectangle features are shown in Figure 3.
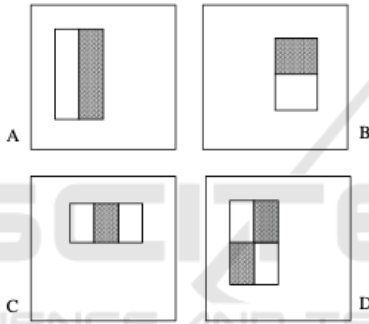
Figure 3: Examples of rectangle features used in Haar cascade method for solder ball detection in silicon wafer images.

For the learning process a variant of Ada Boosting is used both to select a small set of features and train a classifier (Viola and Jones, 2001). Ada Boosting is an algorithm used to boost the classification performance of weak classifiers. Additionally, is designed to select the single rectangle feature which best separates the positive and negative examples. For each feature, the weak learner determines the optimal threshold classification function, such that the minimum number of examples are misclassified.
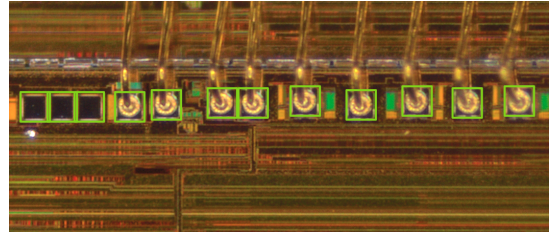
A weak classifier $h_j(x)$ thus consists of a feature f_j, a threshold θ_j, and a polarity p_j indicating the direction of the inequality sign:

$$h_j(x) = \begin{cases} 1 & \text{if } p_j f_j(x) < p_j \theta_j \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where *x* is a 24x24 pixel sub-window of an image. Figure 4 shows the process of solder ball detection using Haar cascade objetct detection.
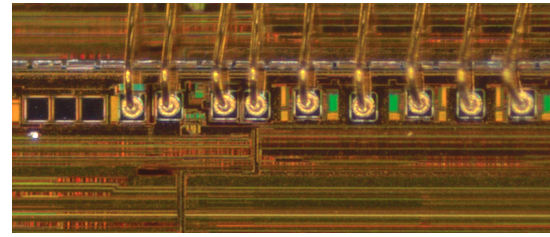
(a)

(b)

Figure 4: Example of solder ball detection using Haar cascade method. Figure 4a corresponds to raw silicon wafer image. Figure 4b corresponds to the solder ball region detection.

3.2 Image Classification

From the segmented solder ball images (*S*), is performed a classification process to identify different solder ball conditions (*B*), like: *i*) correct; *ii*) absence; or *iii*) failure. For this, in this work, is proposed a deep learning based approach to understand patterns and features in different soldering cases.

A CNN is a deep learning architecture strongly used for computer vision applications. CNN models can learn and represent effective features to allow the classification or regression application in real problems. In solder ball classification context the proposed CNN model, unlike other classical approaches, can learns the better features and its representation for the classification stage, even in different scenarios and domains.

The proposed CNN model is composed by two convolutional layers, with 16 filters in first layer and 32 filters in second layer. The filters size in first layer were $(5,5)$, while in second layer were $(9,9)$. The size of the fully-connected layer were 100. The ReLU activation function is used in convolutional layers, with Max Pooling of size window $(2,2)$. In the training stage, are used: the SGD optimization algorithm, learning rate equals to 0.001, with momentum 0.9; for 40 epochs and using a batch size of 32.

A CNN model is used for solder ball classification due to good results achieved in semiconductor automation scenarios (Zhang et al., 2022). The proposed CNN model is also used due to good feature representation learning, depicting distinct and com-
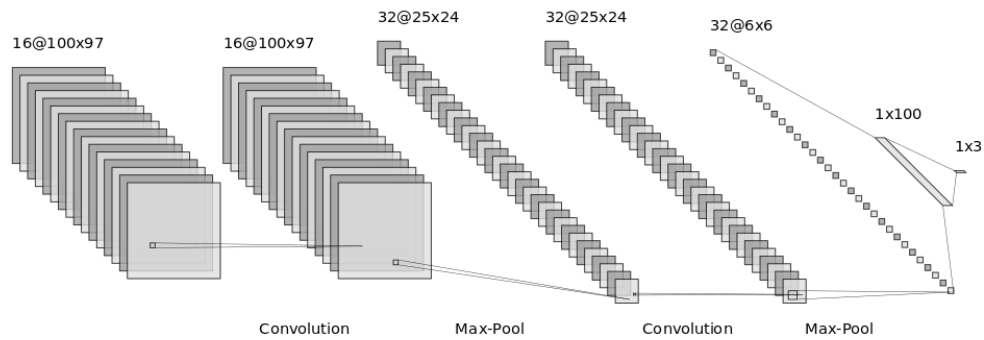
Figure 5: Proposed CNN architecture.

plementary features for modeling of different solder ball conditions, unlike classical approaches. The proposed CNN architecture for the soldering stage, during the semiconductor encapsulation process, can be observed in Figure 5.

4 EXPERIMENTS

In this section we present experimental results and compare the obtained performance against existing approaches.

4.1 Experimental Setup

The proposed experimental setup is composed by an Olympus stereomicroscope SZ61-TR, coupled with a camera SC180, mounted on a XYZ cartesian robot with precise movements. Additionally, a ring light is coupled with the stereomicroscope, providing controlled illumination conditions. A Dell computer with an Intel® Core^{TM} i7-8550U CPU and 32 GiB DDR3-2133 main memory is used to execute the proposed approach (Figure 6).

4.2 Solder Ball Classification Assessment

This experiment evaluates the accuracy of the proposed approach for solder ball classification. Different approaches to tackle the solder ball classification problem are implemented and evaluated. The comparison approaches are: *i*) Local Binary Pattern (LBP) and SVM classifier, with third degree polynomial kernel; *ii*) LBP and Ada Boosting (AB) classifier; *iii*) LBP and Random Forest (RF) classifier; *iv*) Histogram of Oriented Gradient (HOG) and SVM classifier, with third degree polynomial kernel; *v*) HOG and AB classifier; and *vi*) HOG and RF classifier. The comparison techniques were used due
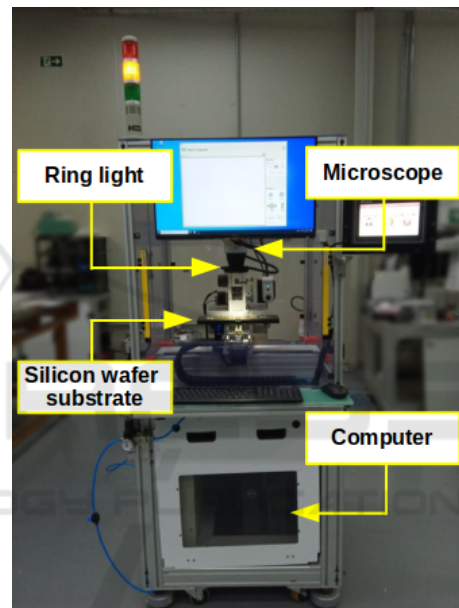

Figure 6: Experimental setup used for automatic visual inspection for solder balls in PCB manufacturing process.

to good results obtained in automatic semiconductor analysis (Iglesias. et al., 2021) and overall automatic visual inspection context (Rahman et al., 2019)(Thielen et al., 2020).

The setting parameters for SVM classifier, with polynomial kernel, were gamma equals to 0.001, *C* equals to 1.0 and kernel degree equals to 3. For AB classifier the setting parameters were, number of estimators equals to 100. For RF classifier the setting parameters were, number of estimators equals to 30 and max depth equals to 30. The parameters tuning for the proposed approach was performed varying a set of parameters to maximize accuracy, during the training and testing stages. Different scenarios changing the number of convolutional layers, the number of filters, the size of filters, the number of fully-connected layers, the size of the fully-connected layers and the

learning rate were experimented.

The classification model training is performed from a set of input images and the testing stage regards another set of input images, since is applied the cross validation 5-fold protocol. The dataset used for the training process, is composed by 1003 images of solder balls, acquired during the semiconductor encapsulation process

The achieved results show that the proposed CNN model outperforms the other classic techniques, as we can observe in Table 1. The better classic performances were obtained using LBP descriptor, depicting texture features, and HOG descriptor, depicting shape features. In addition, were used the RF classifier to detect failures during the soldering stage.

Table 1: Results for solder ball classification. This experiment presents the accuracy for CNN (proposed), HOG and LBP descriptors. Additionally, were used the Random Forest (RF), Support Vector Machine (SVM-Poly3) and Ada Boosting (AB) for classification problem.

Method	Accuracy
LBP + SVM Poly 3	26.208 ± 3.345
LBP + AB	84.345 ± 2.937
LBP + RF	90.627 ± 0.975
HOG + SVM Poly 3	19.342 ± 3.076
HOG + AB	87.241 ± 2.088
HOG + RF	95.114 ± 0.736
Our method	**99.400 ± 0.583**

The proposed approach achieved accurate results, in the solder ball classification process, due to the learning of different filters during soldering process. The CNN process allows the learning of patterns in different contexts and regarding different features. Thereby, some solder ball conditions can be better represented and classified using the convolutional learning process.

4.3 Robustness Evaluation of Solder Ball Classification in Presence of Noise

This experiment evaluates the robustness of the proposed approach for solder ball classification in presence of noise. Two different types of noise are added in solder ball images, Salt and Pepper and Gaussian noises. All the classic techniques, used in experiment 4.2 and the proposed CNN model, are evaluated. In this experiment the added noise simulates the image acquisition process regarding the presence of noise.

For this assessment, the classification model training is performed from a set of images without noise and the testing stage regards another set of images

Table 2: Results for robustness evaluation of solder ball classification, in presence of noise. In this experiment all the considered methods are evaluated for Salt and Pepper noise.

	Salt and Pepper		
Noise density	**0.005**	**0.01**	**0.02**
LBP+SVM	19.342 ± 3.076	19.342 ± 3.076	19.342 ± 3.076
LBP+AB	83.944 ± 2.579	82.450 ± 2.361	75.664 ± 6.442
LBP+RF	90.127 ± 1.214	90.025 ± 2.094	87.134 ± 2.060
HOG+SVM	19.342 ± 3.076	19.342 ± 3.076	19.342 ± 3.076
HOG+AB	76.663 ± 3.336	60.505 ± 7.125	27.508 ± 5.172
HOG+RF	83.452 ± 2.376	74.076 ± 2.700	37.082 ± 4.371
Our method	**97.163 ± 0.707**	**95.275 ± 1.030**	**92.846 ± 3.836**

Table 3: Results for robustness evaluation of solder ball classification, in presence of noise. In this experiment all the considered methods are evaluated for Gaussian noise.

	Gaussian		
Noise density	**0.005**	**0.01**	**0.02**
LBP+SVM	19.342 ± 3.076	19.342 ± 3.076	19.342 ± 3.076
LBP+AB	17.948 ± 2.031	17.748 ± 3.463	18.147 ± 2.459
LBP+RF	19.342 ± 3.076	19.242 ± 3.029	19.142 ± 2.994
HOG+SVM	19.342 ± 3.076	19.342 ± 3.076	19.342 ± 3.076
HOG+AB	15.548 ± 2.271	15.655 ± 1.455	15.951 ± 2.014
HOG+RF	24.025 ± 5.277	20.240 ± 4.440	16.155 ± 1.634
Our method	**81.602 ± 1.748**	**79.430 ± 2.916**	**75.703 ± 3.175**

with added noise. Figure 7 represents solder ball image examples. Figure 7a represents a solder ball without noise. Figure 7b represents a solder ball with Salt and Pepper noise, with 0.02 noise density. Figure 7c represents a solder ball with Gaussian noise, with 0.02 noise density.

The achieved results in this experiment show that the proposed CNN model presents better performance even in the presence of noise, as we can observe in Table 2 and Table 3. Table 2, through the accuracy and variance measures, shows the solder ball classification results for Salt and Pepper noise, for the different used techniques. Table 3, through the accuracy
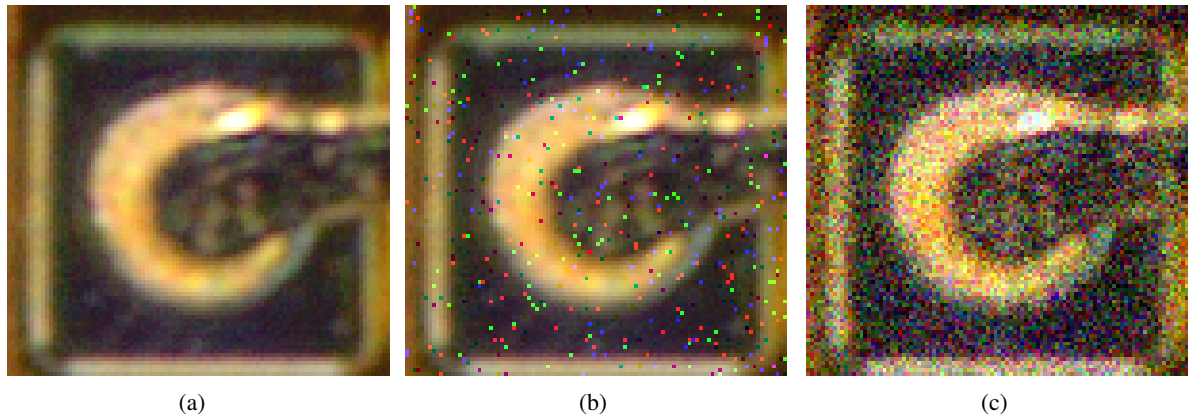
Figure 7: Example of solder ball images in presence of noise. Figure 7a corresponds to raw solder ball image. Figures 7b and 7c correspond to raw image added with Salt and Pepper noise and Gaussian noise, respectively.

and variance measures, shows the solder ball classification results for Gaussian noise, for the different used techniques. Results show that the proposed CNN model outperforms the other classification approaches even in presence of noise, demonstrating the robustness of the proposed approach.

5 CONCLUSION

In this paper, we addressed the problem of soldering visual inspection in semiconductor encapsulation. Unlike other state-of-the-art approaches, our method achieve high accuracy and present the great capacity of inspect very tiny solder ball conditions, providing improvement to the semiconductor encapsulation and production process.

Real-world and simulated experiments involving different classification techniques and simulated noise types have shown that the obtained solder ball classifications are reliable and accurate, considering the obtained results. Additionally, the proposed approach demonstrates robustness, even in presence of noise during image acquisition, and feasibility to real industrial application, once the experiments were carried out in real scenario.

As future work, we intend to combine different classification methods to improve the solder ball classification accuracy. We also intend to concentrate efforts to extend the automatic visual inspection approach to tackle other types of problems related to semiconductor encapsulation. The wire bond analysis and inspection is also a relevant problem we intend to investigate and incorporate in production lines.

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