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Low-cost integrated circuit packaging defect classification system using edge impulse and ESP32CAM

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ABSTRACT

Defects in integrated circuit (IC) packaging are inevitable. Several factors can cause defects in IC packaging such as material quality, errors in machine and human handling operations, and non-optimized processes. An automated optical inspection (AOI) is a typical method to find defects in the IC manufacturing field. Nevertheless, AOI requires human assistance in the event of uncertain defect classification. Human inspection often misses very tiny defects and is inconsistent throughout the inspection. Therefore, this study proposed a low-cost IC packaging defect classification system using edge impulse and ESP32-CAM. The method involves training a deep learning model (i.e., convolutional neural network (CNN)) using a dataset of non-defective and defective ICs on Edge Impulse. For defective ICs, the top surface of the ICs is deliberately scratched to imitate the cosmetic defects. ICs with scratch-free on their top surfaces are considered non-defective ICs. A successfully trained model using Edge Impulse is subsequently deployed on ESP32-CAM. The model is optimized to fit the limited resources of the ESP32-CAM. By using the built-in camera in ESP32-CAM, the trained model can perform a real-time image classification of non-defective/defective ICs. The proposed system achieves 86.1% prediction accuracy by using a 1,571 image dataset of defective and non-defective ICs.

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1. INTRODUCTION

Integrated circuit (IC) assembly and packaging manufacturing involves several processes such as die attach, wire bond, moulding, plating, marking, trim & form. The end product of the ICs must be fully functional and free from defects before the products ship to the customers. Nevertheless, defects in IC packaging are inevitable due to several factors such as material quality, errors in machine and human handling operations and non-optimized processes [1]. Common practice in IC manufacturing of using automated optical inspection (AOI) and manual inspection often lead to defect IC escapee and inconsistency in defective/non-defective classification [2]. One of the potential methods to improve IC defects identification and analysis is to used machine learning or deep learning techniques (i.e., image classification) [3].

Several techniques of IC defect classification using machine learning or deep learning techniques have been proposed in the past. Earlier, Chen *et al.* [4] proposed a defect classification algorithm for IC photomask using principle components analysis (PCA) and support vector machine (SVM). PCA is used for feature extraction and subsequently, the extracted feature are fed to the SVM to perform the IC photomask defect classification. In a study, Le *et al.* [5] proposed a technique to detect and classify ball-grid-array (BGA) defects using patch-based modified YOLOv3 technique. BGA defect images with size of 1,450×1,450 pixels undergo patch extraction using scan-line method where each patch covering an area of 320x320 pixels. The full size of BGA images and the corresponding patches are used to perform BGA defect classifications. Elsewhere, YOLOv5 technique is used to classify defect of GaAs IC chip [6], IC lead frame defect [7], and IC socket pin defect [8].

Recent works were focusing on wafer map defect classification [9]–[14]. There are nine wafer defect classes include center, donut, edge-location, edge-ring, random, location, near-full, scratch and none. Diverse techniques have been used for classifying wafers into their corresponding defect type such as convolutional neural network (CNN) [14], [15], deep selective learning [16], reduced-weight architecture based on depthwise separable convolutions [17], multi-scale depthwise separable convolutions [13], transfer learning [10], ResNet architecture [12], and unsupervised learning [11]. In another work, Luo *et al.* [18] studied the detection and classification of through silicon via (TSV) defects in three-dimensional (3D) IC using k-nearest neighbours (KNN) algorithm. Signal delay and frequency are used as feature vectors to perform the classification algorithm. The wire bonding defect classification using deep learning EfficientNetB0 V2 technique is proposed in [19]. Defects such as lifted bond, broken wire, non-stick on pad (NSOP), and double bond are considered in wire bonding defect classification.

Based on all the above, the previous studies focused the defects on wafer, IC photomask, wire bond, BGA, lead frame, and socket pin. There was no study on developing the IC packaging defect classification system. This paper focuses on developing the low-cost IC packaging defect classification system using Edge Impulse and ESP32-CAM. Cosmetic defect such as scratches on IC mold compound surfaces is considered in this study. The proposed system is expected to increase the yield, productivity and quality of the IC manufacturing process.

2. METHODOLOGY

In this section, the methodology to design the low-cost IC packaging defect classification system using Edge Impulse and ESP32-CAM is described. Figure 1 illustrates the top-level block diagram of the low-cost image classification system using ESP32-CAM. To design the proposed system as depicted in Figure 1, this project is divided into three main parts which are training the dataset with suitable deep learning algorithm in Edge Impulse [20], deploying the Arduino library generated by Edge Impulse in ESP32-CAM, and prediction accuracy evaluation.

First, the dataset of defective and non-defective ICs is created. For defective ICs, the top surface of the ICs are deliberately scratched to imitate the cosmetic defects as can be seen in Figure 1. ICs with scratch-free on their top surfaces are considered as non-defective ICs. In total, 1,031 images of defective ICs and 540 images of non-defective ICs are captured using a smart-phone camera. Subsequently, this dataset is loaded into an Edge Impulse with 80%/20% train/test split ratio. MobileNetV2 CNN is chosen as a training algorithm since it offers the best performance in image classification application [21], [22] and it is suitable to be used for low-power and lightweight micro-controller [23], [24]. The trained model can be deployed on micro-controller by generating the Arduino library in Edge Impulse.

Next, the hardware of IC defect classification system is developed. Hardware components involved which are ESP32-CAM, TFT ST7735S, USB to RS232 TTL converter (USB-TTL), 3.3V/5V MB102 breadboard power supply module, and push-button switch. In our study, an ESP32-CAM is used for computing resources as it offers lightweight, low-power, and low-cost performance [25]. Moreover, it has a built-in camera, hence, no additional camera module is needed. TFT ST7735S is used to display the image of ICs while USB-TTL is used to deploy the Arduino library on ESP32-CAM. Finally, the real-time image classification is performed to evaluate the predictability performance in classifying the defective and non-defective ICs.

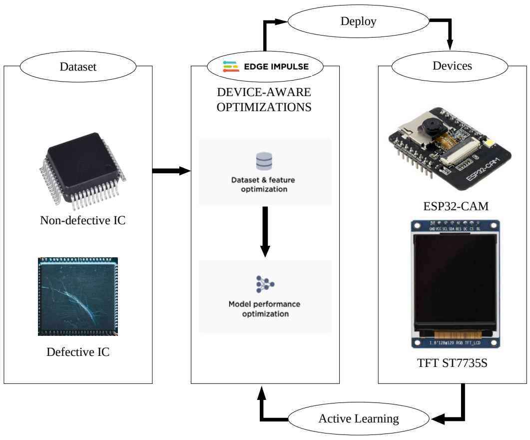


Figure 1. Top level block diagram of low-cost image classification system

3. RESULTS AND DISCUSSION

3.1. Edge impulse image classification training

A total of 1,571 dataset which consists of 1,031 defective IC images and 540 non-defective IC images are loaded into the Edge Impulse. The dataset is split according to 80%/20% train/test split ratio. These images are labeled according to their description either *defect* or *non defect* labeling. The learning parameters of image classification training are set according to the methodology description in section 2.

Figure 2 depicts the training performance of classifying the defective and non-defective ICs. The trained model has a higher predictability on classifying defective ICs (99.4%) as compared to non-defective ICs (64.6%). As the number of defective IC images are much higher than non-defective IC images, hence the CNN learning rate is better in predicting the defective ICs. Overall, a prediction accuracy of 86.1% is achieved in classifying the defective and non-defective ICs. Subsequently, the successful trained model is configured to be deployed in ESP32-CAM and the image classification Arduino library is generated.

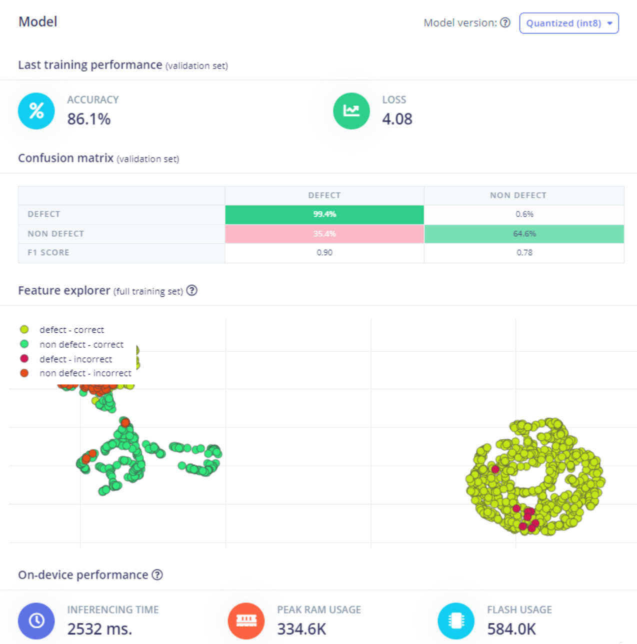


Figure 2. Edge impulse classification training performance

3.2. Hardware setup

Figure 3 depicts the hardware configuration to perform the classification of defective and non-defective ICs. Four major components involved which are ESP32-CAM, TFT ST7735S, USB-TTL, and 3.3V/5V MB102 breadboard power supply module. Tables 1 and 2 list the pin connections of TFT ST7735S and USB-TTL to ESP32-CAM, respectively. The hardware configuration on breadboard is verified using the Arduino library generated in section 3.1 and it is successfully performs real-time IC defect classification.

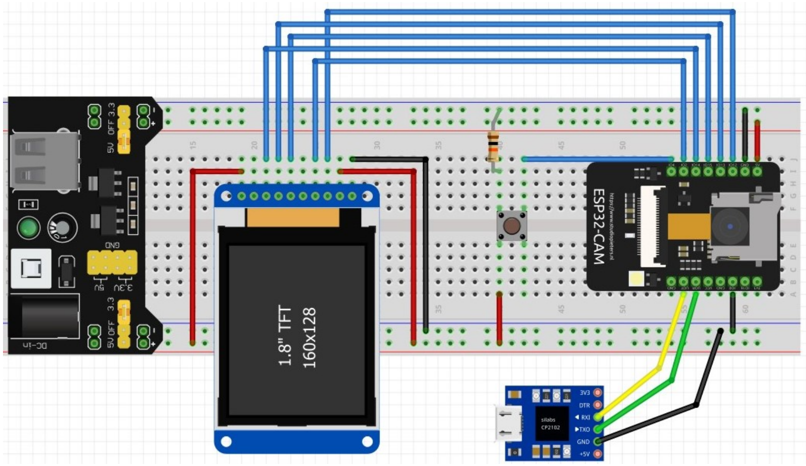


Figure 3. Circuit configuration on breadboard

Table 1. TFT ST7735S pins to ESP32-CAM pins

TFT ST7735S	ESP32-CAM
SCK (SCL)	GPIO 14
MOSI (SDA)	GPIO 13
RESET (RST)	GPIO 12
DC	GPIO 2
CS	GPIO 15
BL (back light)	3.3V

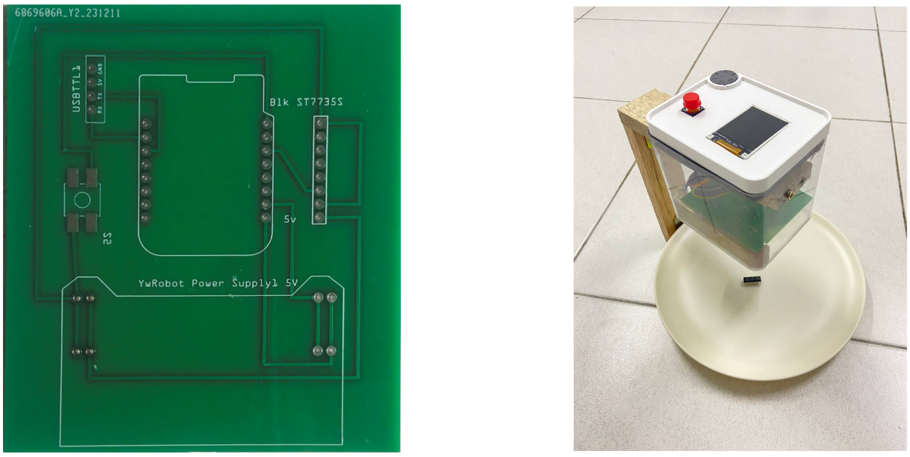
Table 2. USB-TTL pins to ESP32-CAM pins

USB-TTL	ESP32-CAM
TXO	GPIO 3 (U0RXD)
RXI	GPIO 1 (U0TXD)
GND	GND

Based on the hardware configuration on breadboard, the printed circuit board (PCB) is manufactured as depicted in Figure 4(a). Figure 4(b) illustrates the assembled hardware on PCB and the built prototype of IC packaging defect classification system. The prototype works as follows. First, the user positions the IC on the plate, exactly below the built-in camera of ESP32-CAM module. The IC's image is immediately displayed on thin-film-transistor (TFT) screen. Subsequently, the red push-button is pressed to start the classification process. The user able to check the defective or non-defective IC's image and the classification result on the TFT screen.

3.3. Classification analysis

Table 3 lists the results of a real-time IC classification using 60 dataset which consists of 30 defective ICs and 30 non-defective ICs. The developed IC classification system able to predict the defective and non-defective ICs with 86.76% and 76.67% prediction accuracy, respectively. On average, the achieved prediction accuracy is 81.67% which slightly lower than the prediction accuracy during the training process. The prediction accuracy degradation is caused by the environmental and camera resolution variations during dataset collection (i.e., smart-phone camera) and real-time image classification (i.e., built-in ESP32-CAM camera).



(a) (b)

Figure 4. A prototype of IC packaging defect classification system (a) PCB traces and (b) integrated hardware

Table 3. Real-time IC classification performance using the trained model

Samples	Number of dataset	Correct Classification	Percentage(%)
Defective	30	26	86.67
Non-defective	30	23	76.67

4. CONCLUSION

In this paper, a low-cost IC packaging defect classification system using Edge Impulse and ESP32-CAM has been proposed. A total of 1,571 dataset which consists of 1,031 defective IC images and 540 non-defective IC images has been used for training and testing processes. A split ratio of 80%/20% test/train and MobileNetV2 CNN architecture are used to build the classification model. The successful trained model using Edge Impulse achieves a prediction accuracy of 86.1%. Subsequently, the image classification Arduino library of the trained model is generated and deployed in ESP32-CAM, a prototype of IC packaging defect classification system. The prototype successfully performs a real-time IC defect classification with accuracy of 86.67% (defect ICs) and 76.67% (non-defect ICs), respectively.

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